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Global image completion with joint sparse patch selection and optimal seam synthesis

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ABSTRACT

This paper presented a global exemplar-based image completion method for filling large missing or unwanted regions in an image. Based on three proposed completion rules, 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 sparse patch subspace searching and optimal seam synthesis respectively. The patch subspace is learned with the statistics of geometric transformation relationships of similar patches. Moreover, E step combines image patch synthesis and coherent correction simultaneously. We analyzed the proposed 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.

1. 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 [1–6] 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 regions or structure images. Although, they lead to blurred results when dealing with large defect regions or complex textures due to lack of semantic texture or structure synthesis.

Exemplar-based methods [7–23] perform more effectively for large missing regions. 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 fashions.

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Criminisi et al. [7] and Drori et al. [8] 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 lead to color and structure incoherent. To ensure structure continuity, Jia and Tang [9] performed image segmentation and edge connection to complete image structures. The completed results are dependent on image segmentation. Sun et al. [10] interactively provided significant structure information by drawing some curves from the known region to unknown region, which guides structure propagation in completion process. Xu and Sun [11] used structure sparsity to determine the patch priority. All the methods above perform completion in greedy fashions by determining 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 fashions cannot correct the synthesized patches backwardly, which results in error propagation.

Unlike methods with greedy fashions, some methods perform completion in global fashions. Komodakis and Tziritas [12] use belief propagation algorithm to optimize a global energy function. Wexler et al. [13] define and optimize a spatial and temporal coherence function to complete video. The cost energy functions defined in these methods usually encourage 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. [14] 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. [15] 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 unknown pixels in a query image block. Broll [16] presented an approach for high quality real-time image and video inpainting which allows for the manipulation of live video streams. He and Sun [21] proposed an approach to constrain the selection of known patches through the 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. Ge et al. [23] proposed a global completion method to perform patch matching and synthesis in a unified way.

Texture generation is another key completion issue and 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 and Freeman [24] performed quilting to ensure similar overlap existing in adjacent patches. Kwatra et al. [25] handled overlapped areas using graph cut based optimization. Agarwala et al. [26] corrected the color difference between overlapped regions using gradient domain fusion [27]. Ge et al. [28] performed seamless stitching with total variation gradient fusion.

In this paper, we proposed a global exemplar-based image completion method to restore the large missing or unwanted 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 performing optimal patch selection and optimal seam synthesis. Compared with our previous work [23] we introduced a sparse patch subspace learning method to enhance the selection for similar patch matching. The theory analysis on the global energy function and the optimization method was discussed. Simulation experiments compared with diffusion-based method [1], greedy exemplar-based completion method [7] and several state-of-the-art image completion methods [13–16] demonstrate the advantages of our method in ensuring globally coherence of completion results.

2. Global optimization of completion problem

2.1. Basic concepts

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 adjacent target patches are overlapped with $\frac{h}{2} \times \frac{w}{2}$. 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.

2.2. Completion rules

To meet the requirements of visual integrity and consistency, 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 $i = 1, \ldots, m$ represents index of the target patch. Target patch X_n^i should be similar to Z_n^i selected from $\{Z_p\}$, thus maximizing $sim(Z_n^i, X_n^i)$ in which $sim(\cdot,\cdot) \in (0,1]$ measures the similarity between two patches, and equals to 1 when two patches are just the same.