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Structure-preserving texture filtering for adaptive image smoothing

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ABSTRACT

Extracting meaningful structures from images with complicated texture patterns is challenging since it is hard to separate structure from texture with similar scale or intensity contrast. In this paper, we propose a structure-preserving bilateral texture filtering algorithm to smooth texture while preserving salient structures. We design a *dual-scale patch toggle* scheme. That is, two-scale patches are exploited to represent pixels alternatively, the smaller ones for pixels located at structure edges and the bigger ones for pixels in textural regions, and DASM (Directional Anisotropic Structure Measurement) on each pixel is estimated to select which type of patch for it. Our algorithm is based on the framework of joint bilateral filtering, so it is fast, easy to implement, yet effective for adaptive image smoothing. In particular, our approach outperforms previous methods in terms of preserving small structures. The proposed method achieves excellent results that illustrate its effectiveness and efficiency.

1. Introduction

Texture filtering is a fundamental yet powerful operation in computational photography and computer vision. It aims to smooth texture in an image while preserving structure as well as possible, which is of immediate use for a variety of applications such as image editing, tone mapping, artistic rendering, etc. The ultimate solution is to design an ingenious metric and according scheme that can separate meaningful structures from fine details effectively. However, this is challenging due to the variety and complexity of image contents.

Structure-preserving filtering has been gaining much attention all along in related communities. A large number of classic methods assume local contrast of image intensity as structure measurement [1–4]. Such methods can preserve structures of high contrast well in the filtering process, but fail to flatten texture with comparable or higher contrast. Subsequently, much effort has been dedicated for more sophisticated metric free of contrast scale dilemma, such as oscillations of local extrema [5], total variation (TV) with intensity gradients [6,7] and patch-based local covariance [8]. These methods exhibit commendable strength in adaptive smoothing, whereas they still suffer undesirable artifacts and computational cost. Another trend of research is to explore how to exploit existing structure measurements for guiding texture filtering. As a representative, bilateral texture filtering [9] empowers itself with *patch shift*, a novel scheme of utilizing intuitive structure measurement to discriminate structure and texture. This method competes with previous methods on the effectiveness of adaptive smoothing.

This paper follows this trend, but turns to a new manner, *dual-scale patch toggle*. Namely, we use patches of two different sizes to represent pixels, the smaller for pixels on structure edges and the bigger for pixels in texture regions, and adopt the directional anisotropic structure measure (DASM) [10] on each pixel as structure/texture indicator for selecting which type of patch. Similarly, our algorithm incorporates texture information into the range kernel of a joint bilateral filter, so it is fast, easy to implement, yet effective for adaptive image smoothing. Comparatively, our proposed method preserves prominent edges, small structures and shading better during the process of texture filtering, as our results illustrated. Fig. 1 exhibits the overall process of our approach. Additionally, we also demonstrate the applicability of our method on several related applications, such as detail manipulation, inverse halftoning, etc.

2. Related work

Bilateral filtering [1] is one of the most classic non-linear operators for edge-preserving image smoothing and decomposition. It has been widely applied to a variety of computational photography applications. However, this filter cannot handle texture images where their scale of color variation may not be small. Subsequently, more sophisticated edge-preserving filters are developed, such as weighted least squares (WLS) [2], edge-avoiding wavelets

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(a) (b) (c) (d) (e)

Fig. 1. Overall process and intermediate images of our structure-preserving bilateral texture filtering. (a) Input Image *I*. (b) Blurred Image B_0/B_1. (c) DASM Map *M*. (d) Guidance Image *G*. (e) Output Image *J*.

[11], local histogram filtering [12],domain transform [3], guided filter [13], local Laplacian filtering [14], L_0 gradient minimization [4], and rolling guidance filter [15]. Although they overcome the defect of bilateral filtering by forcing the filtered image to be smooth everywhere except at regions having large variation, they still build structure measurement on intensity contrast or gradient magnitude. Therefore, the ongoing smoothing processes inherently can not separate prominent structures from image details or textures well enough.

In view of this limitation, Subr et al. [5] define detail as oscillations between local extrema and smooth an image by averaging the extremal envelopes. Since taking the oscillatory behavior of textures into consideration, this framework provides better results compared to local contrast based filters aforementioned. However, in practice, it might fail to cope with image regions containing both texture and meaningful structures.

On the other hand, Total variation (TV) [16] has proven to work well on filtering irregular textures by imposing TV regularizer to preserve large-scale edges. The variations of TV regularization was further developed to achieve better quality and efficiency [6,7,17]. In particular, Xu et al. [7] proposed *relative total variation* (RTV), a spatially-varying total variation measure that contributes to boost the quality of texture-structure separation. Alternatively, Karacan et al. [8] propose a patch-based texture removal method that uses covariance matrix associated with each image patch as the description and identification of texture feature, leading to better performance in differentiating salient structures and texture. However, these methods share the drawback that the performance is sensitive to the scale of image feature, i.e., structures disappearing whose sizes are coincident with those of texture.

Recently, Zang et al. [10] develop a novel *directional anisotropic structure measurement* (DASM) for adaptive image smoothing. Although they obtain much better results of structure-preserving texture removal attributed to this metric, their empirical mode decomposition (EMD) based smoothing framework is harder to accelerate compared to kernel-based filtering.

Despite the way of seeking for more and more sophisticated definition of structure/texture, another trend is to focus on innovating the scheme of utilizing these definition to carry out texture filtering. Cho et al. presented *patch shift* [9] to capture texture information from the most representative image patch clear of structure edges. Although adopting not-so-sophisticated *modified Relative Total Variation* (mRTV) as structure/texture indicator, patch shift helps preserve structures very well. However, the combination of mRTV and patch shift incurs side effects such as blurring of structures, over-sharpening of edges, etc. Lin et al. [18] propose a scheme of double-scale representation of pixels to overcome the drawback of *patch shift*. However, their method necessitates much trial and experimental experience to setup key parameters. We improve their scheme further and adopt the more robust DASM as our structure/texture discriminator, which facilitates the automation of parameters setting.

3. Overview

We build our algorithm on the intuitive yet efficient framework of joint bilateral filtering, and it is simple and fast, as well as effective in smoothing textures and preserving structures. Fig. 1 exhibits the overall procedure of our approach.

Given an image *I*, our approach firstly creates a guide image *G* based on its two blurred version B_0, B_1 of *I*, obtained by performing box filtering on *I* with $e \times e$ kernel and $k \times k$ kernel respectively ($e \le k$). As can be seen, in B_0 (Fig. 1(b) *left-side*), most structure edges are represented by small $e \times e$ patches fairly clearly, whereas other regions are larger $k \times k$ patches in B_1 (Fig. 1(b) *right-side*). Virtually, small patch width *e* is prescribed to preserve structures, while big patch width *k* determines how large the scale of textures is to be smoothed. The subsequent question is which type of patch is suitable for representing a pixel in the following process of texture filtering. That is, G_p, each element of *G*, is toggling between two candidates: B_{0p} and B_{1p}. We adopt the directional anisotropic structure measurement (DASM) at each pixel of *I* as the indicator for assigning. Eventually, the whole flow is boiled down to a scheme of *dual-scale patch toggle*.

Next the joint bilateral filter is applied to image *I*, using *G* as the guide image to create an output image *J*, as shown in Fig. 1(d). *J* is assigned to *I* as an input image for next iteration. Finally, an experimental result is achieved at the given iteration.

The following Section 4 introduces our proposed approach in detail. Section 5 gives our experimental results and comparisons with state-of-the-art and demonstrates several applications of our method. The paper is concluded with Section 6.

4. Structure-preserving bilateral texture filtering

To the algorithmic complexity involved with optimization-based or EMD-based image smoothing techniques, we prefer a clear and concise scheme that produces amendable results from input images intuitively and efficiently. So we adopt joint bilateral filter as our underlying framework.

Given a scalar-valued input image *I*, bilateral filter computes an output image *J* by

$$J_p = \frac{1}{k_p} \sum_{q \in \Omega_p} f(||q - p||) g(||I_q - I_p||) I_q, \tag{1}$$

where k_p is a normalizing term. The output value J_p at pixel *p* is a weighted average of I_q in the neighborhood Ω_p. The weight of pixel *q* depends both on the Euclidean distance to *p* and on the intensity difference. It is evaluated with the spatial kernel *f* and the range kernel *g*, which are typically Gaussian functions.

Although bilateral filter is already an edge-preserving filter which can smooth images and reduce noise. it cannot handle texture images where their scale of intensity variation may not be small. Therefore, we substitute a texture description image $(G_p - G_q)$ for the input image $(I_p - I_q)$ in the range kernel *g*; it comes to