A Fast Wavelet-Based Seam Carving Algorithm for Image Resizing

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ABSTRACT--- This paper presents a fast image resizing algorithm based on wavelet trees in the framework of the benchmark image coder known as set partitioning in hierarchical trees (SPIHT). It takes full advantage of the hierarchical structure of wavelet trees to gradually remove seams of insignificant wavelet trees in a scale recursive manner. Experimental results show that the proposed algorithm is preferable especially in terms of computation time.

Keyword---- Image resizing, Seam carving, Wavelet tree, SPIHT

1. INTRODUCTION

Various mobile devices such as smart phone, digital camera, and tablet PC have been successfully introduced into the market. One of the pressing challenges is that the size, aspect ratio, and resolution of images must be tailored to a specific device. Traditional image resizing methods, e.g. cropping and uniform scaling can be used to fit diverse screens of the devices; however, it often results in annoying distortions and loss of important information [1]. Avidan and Shamir proposed the seam carving (SC) algorithm for content-aware image resizing [2]. It gradually removes seams of less important pixels to adjust image sizes. Later, Shamir and Sorkine proposed the forward energy map to improve the performance of SC [3]. Conger et al. proposed seamlet transform via local circular convolution with wavelet filters for multi-seam carving [4]. In [5], the scale invariant feature transform (SIFT) was used to measure the distance between images with different sizes, based on which the resized image was first obtained by gradually removing seams of insignificant pixels until the SIFT distance from the original image was greater than a given threshold; if need be, further resizing can be fulfilled by simple scaling.

Wavelet transform provides an efficient way to represent images at multiple scales [6]. Mishiba and Ikehara proposed a simple method for shrinking gray-scale images in the wavelet domain [7]. It removes seams of insignificant wavelet coefficients based only on the lowest-frequency subbands; however, the correlation between successive subbands known as the parent-child relationship is beneficial especially for visual applications. Said and Pearlman organized wavelet coefficients into hierarchical trees based on the parent-child relationship for image compression [8]. In this paper, we propose seam carving in wavelet trees, which gradually removes insignificant wavelet trees in the scale recursive manner.

2. PROPOSED SEAM CARVING IN WAVELET TREES

For effective displaying of images on diverse screens with arbitrary sizes and aspect ratios, the region of interest (ROI) should be intact as much as possible while resizing an image. In this section, we review the content-aware image resizing algorithm known as the seam carving (SC) algorithm [2], the hierarchical structure of wavelet trees, and propose a fast scale-recursive image resizing algorithm in wavelet trees.

2.1 The SC algorithm

In [2], a vertical/horizontal seam is defined as a path of 8-connected pixels crossing an image from top to bottom/left to right. Avidan selected the pixels to be removed based on the gradient energy function:

$$e\left(I\left(i, j\right)\right) = \left|\frac{\partial}{\partial x}I\left(i, j\right)\right| + \left|\frac{\partial}{\partial y}I\left(i, j\right)\right|, \text{ where } I\left(i, j\right) \text{ is an image pixel at coordinates } \left(i, j\right), \frac{\partial}{\partial x} \text{ and } \frac{\partial}{\partial y} \text{ are } \left(i, j\right) = \left|\frac{\partial}{\partial x}I\left(i, j\right)\right| + \left|\frac{\partial}{\partial y}I\left(i, j\right)\right|, \text{ where } I\left(i, j\right) \text{ is an image pixel at coordinates } \left(i, j\right), \frac{\partial}{\partial x} \text{ and } \frac{\partial}{\partial y} \text{ are } \left(i, j\right) = \left|\frac{\partial}{\partial x}I\left(i, j\right)\right| + \left|\frac{\partial}{\partial y}I\left(i, j\right)\right|, \text{ where } I\left(i, j\right) \text{ is an image pixel at coordinates } \left(i, j\right), \frac{\partial}{\partial x} \text{ and } \frac{\partial}{\partial y} \text{ are } \left(i, j\right) = \left|\frac{\partial}{\partial x}I\left(i, j\right)\right| + \left|\frac{\partial}{\partial y}I\left(i, j\right)\right|, \text{ where } I\left(i, j\right) \text{ are } \left(i, j\right) = \left|\frac{\partial}{\partial x}I\left(i, j\right)\right|, \text{ where } I\left(i, j\right) = \left|\frac{\partial}{\partial y}I\left(i, j\right)\right| + \left|\frac{\partial}{\partial y}I\left(i, j\right)\right| + \left|\frac{\partial}{\partial y}I\left(i, j\right)\right|, \text{ where } I\left(i, j\right) = \left|\frac{\partial}{\partial y}I\left(i, j\right)\right| + \left|\frac{\partial}{\partial y}I\left(i,$$

gradient operators in the horizontal and vertical directions, respectively. The cost $E(s^x)$ of a vertical seam s^x is

defined as $E(\mathbf{s}^{x}) = \sum_{i=1}^{n} e(\mathbf{s}^{x}_{i})$, and the optimal vertical seam \mathbf{s}^{*} is thus the one with minimum cost given by $\mathbf{s}^{*} = arg \min E(\mathbf{s}^{x})$.

2.2 Wavelet tree

A finite-energy signal can be efficiently decomposed into a set of frequency channels, which have the same bandwidth on a logarithmic scale, by using wavelet transform. After 1-level wavelet transform, the input image is decomposed into four subbands: LL_1 , HL_1 , LH_1 , and HH_1 representing the approximation image (consisting of scaling coefficients) and detail images (consisting of wavelet coefficients) in the horizontal, vertical, and diagonal directions, respectively, at the next coarser scale 1. The approximation image can be recursively decomposed to generate the approximation images and detail images at successively coarser scales. Moreover, the original image can be exactly reconstructed from the approximation image LL_L at the coarsest scale L and the detail images HL_ℓ , LH_ℓ and HH_ℓ ; $\ell = 1, 2, ..., L$ via L-level inverse wavelet transform.

The spatially correlated wavelet coefficients of an image can be organized into hierarchical trees called wavelet trees across scales [8]. The leaves of a wavelet tree are wavelet coefficients at the finest scale. Each non-leaf node can be a parent node with four children at the next finer scale. With the hierarchical structure of wavelet trees, many efficient algorithms can be found in the literature, for example the set partitioning in hierarchical trees (SPIHT) algorithm, which has been considered as one of the most successful image coders [8].

2.3 Proposed algorithm

As SC is a pixel-based algorithm, if often causes the time consuming problem. To speed up the process of resizing images, we propose a fast multiscale seam carving with wavelet trees.

In SPIHT, the scaling coefficients and wavelet coefficients at the coarsest scale are initially stored in the list of insignificant pixels (LIP); the wavelet trees represented by their respective roots are stored in the list of insignificant sets (LIS). By comparing with a sequence of successively smaller thresholds, the significant nodes stored in LIP are identified and then removed to the list of significant pixels (LSP); the significant entries of LIS are also identified in order, which are actually significant wavelet trees and so further partitioned into significant nodes stored in LSP, insignificant nodes stored in LIP, and insignificant (sub-) wavelet trees stored in LIS. Motivated by the success of SPIHT, we propose removing seams of insignificant wavelet trees from LIS in the scale recursive manner for the image resizing applications. For the sake of simplicity, we combine the spatially correlated scaling coefficients and wavelet trees to form super-wavelet trees. A vertical seam of wavelet trees at scale ℓ is defined as

$$\boldsymbol{s}_{\ell}^{x} = \left\{ \boldsymbol{s}_{\ell,i}^{x} \right\}_{i=1}^{n_{\ell}} = \left\{ \left(\boldsymbol{x}(i), i \right) \right\}_{i=1}^{n_{\ell}}, \text{ s.t. } \forall i, | \boldsymbol{x}(i) - \boldsymbol{x}(i-1) | \leq T$$
(1)

where $n_{\ell} = \frac{n}{2^{\ell}}$ is the height of wavelet subbands at scale ℓ , n is the height of the original image, and (x(i), i) is the

coordinates of the spatially correlated scaling coefficient of a super-wavelet tree. The definition of a horizontal seam of wavelet trees is similar. To avoid carving out significant descendants, i.e. the spatially correlated significant wavelet coefficients at finer scales, while removing wavelet trees from LIS, the following energy function $e(t_{\ell}(i, j))$ of a super-wavelet tree $t_{\ell}(i, j)$ at coordinates (i, j) at scale ℓ has been considered on account of the parent-child relationship.

$$e\left(t_{\ell}(i, j)\right) = \alpha \cdot \sum_{d} S\left(t_{\ell}^{d}(i, j)\right) + \beta \cdot G\left(c_{\ell}(i, j)\right)$$
(2)
$$S\left(t_{\ell}^{d}(i, j)\right) = max \left| D\left(t_{\ell}^{d}(i, j)\right) \right|$$
(3)

$$G\left(c_{\ell}\left(i,\,j\right)\right) = \left|\frac{\partial}{\partial x}c_{\ell}\left(i,\,j\right)\right| + \left|\frac{\partial}{\partial y}c_{\ell}\left(i,\,j\right)\right| \tag{4}$$

where $t_{\ell}(i, j)$ consists of the spatially correlated scaling coefficient $c_{\ell}(i, j)$ and three wavelet trees $t_{\ell}^{d}(i, j)$; $d \in \{HL, LH, HH\}$ in the horizontal, vertical, and diagonal directions, respectively, $S(t_{\ell}^{d}(i, j))$ represents the significance of $t_{\ell}^{d}(i, j)$, $D(t_{\ell}^{d}(i, j))$ is the descendants of $t_{\ell}^{d}(i, j)$, and $G(c_{\ell}(i, j))$ is the

gradient of $c_{\ell}(i, j)$. Given $e(\cdot)$, the significance $E(s_{\ell}^{x})$ of a vertical seam s_{ℓ}^{x} at scale ℓ is defined as

$$E\left(\mathbf{s}_{\ell}^{x}\right) = \sum_{i=1}^{n_{\ell}} e\left(t_{\ell}\left(x(i), i\right)\right)$$
(5)

The least significant seam s_{ℓ}^* at scale ℓ is the optimal one to be removed from LIS as follows.

$$\boldsymbol{s}_{\ell}^{*} = \arg\min_{\boldsymbol{s}_{\ell}^{x}} E\left(\boldsymbol{s}_{\ell}^{x}\right) \tag{6}$$

It can be efficiently found via dynamic programming using the following cumulative minimum energy map $M(i, j) = e(t_{\ell}(i, j)) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$ (7)

3. EXPERIMENTAL RESULTS

The bi-orthogonal wavelet with 5/3-coefficient filter set (adopted in the JPEG2000 standard) was used to construct wavelet trees. The number of tree levels *L* was 3. Weights $\alpha = 2$ and $\beta = 1$. The proposed algorithm was implemented in Matlab running on a PC equipped with an Intel® CoreTM i7 1.73 GHz CPU.

Figure 1 shows the idea of the proposed algorithm. To begin with, as a scale recursive algorithm, seams of insignificant wavelet trees are discarded at the coarsest scale, and therefore thick seams of corresponding pixels marked with black lines are removed from the original image. The results of discarding seams of insignificant wavelet trees at successively finer scales are also given. As the equivalent number of removing one-pixel-wide seams of image pixels is greater than the total number of discarding seams of insignificant wavelet trees, the speed of resizing images can be improved significantly by multi-scale seam carving in wavelet trees. Figure 2 shows the running time required to shrink the width of the input image with various sizes by 50% using the proposed algorithm and the SC algorithm. It is noted that the larger the input image size is, the more advantageous the proposed algorithm is in terms of computation time.

Visual comparison is given in Figure 3; the original images are shown in the first row. The width of the first test image is reduced by 25%; the width and height of the rest of the test images are both reduced by 25%. It is evident that there are noticeable distortions in the resized images using the SC algorithm (without the aid of saliency map). In contrast, the proposed algorithm ameliorates the distortion of ROI due largely to the use of wavelet coefficients as salient features.

4. CONCLUSION

The pixel-based seam carving (SC) algorithm is suitable for content-aware image resizing, however it is likely to cause intensive computations. Wavelet transform provides an efficient multi-resolution analysis, in which images can be represented by hierarchical wavelet trees. The proposed algorithm, which incorporates SC in the framework of SPIHT, gradually removes seams of insignificant wavelet trees in a scale recursive manner. It improves the speed of seam carving at no cost of degrading image quality. In addition, as both the proposed algorithm and the SPIHT algorithm are based on the parent-child relationship of wavelet trees, it is thus encouraging to modify the SPIHT algorithm for the merit of content-aware spatial scalability; it is an ongoing research.

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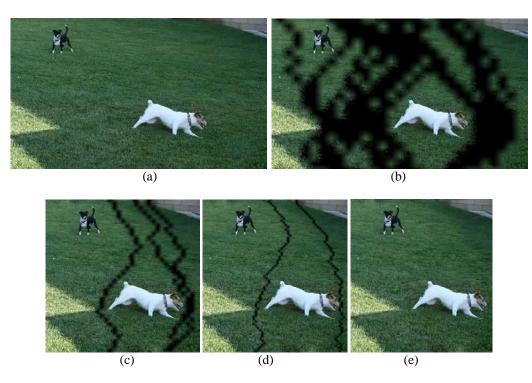


Figure 1: Demonstration of the proposed algorithm, (a) original image, (b) \sim (d) vertical seams of image pixels (marked in black lines) corresponding to seams of insignificant wavelet trees at the coarsest scale 2, scale 1, and scale 0, (e) the final resized image.

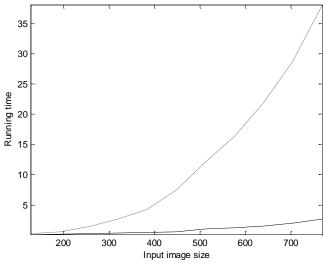


Figure 2: Running time required to shrink the width of the input image with various sizes by 50% using the proposed algorithm (solid line) and the SC algorithm (dotted line), respectively.

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Figure 3: Test images (1^{st} row) followed by the resized images using the SC algorithm (2^{nd} row) and the proposed algorithm (3^{rd} row) .