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An effective method to detect seam carving

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ABSTRACT

Seam carving, also known as content-aware image resizing, is the most popular image resizing algorithm nowadays. Therefore, detecting seam carving has become an important topic in image forensics. In this paper, an advanced statistical model, consisting of local derivative pattern, Markov transition probabilities, and subtractive pixel adjacency model, is proposed to determine if an image has been seam carved or not. The performance of the proposed feature set can be further improved, and the feature set's dimensionality can be largely reduced by utilizing linear support vector machine (SVM) based recursive feature elimination. With the linear SVM classifier, the experimental works have demonstrated that the proposed approach can successfully detect seam carving. It outperforms the state-of-the-art in general; in particular at the low carving rate cases, such as 5%, 10% and 20%, the average detection accuracy has been boosted from 66%, 75% and 87% to 81%, 90% and 96%, respectively. On detecting seam carving in JPEG images and geometrical transformed uncompressed images, the proposed approach has also shown promising performance.

1. Introduction

Due to the comprehensive usage of digital images, the image editing technologies have been developed tremendously in the past decades. However, the advanced technologies not only benefit individuals on image editing but also benefit individuals with illegal purposes such as perjury. Thus, image forensics [11] has increasingly attracted wide attention and played an important role in our daily life. In this paper, an advanced statistical feature model is proposed to detect seam carving, which is the most popular content-aware image resizing algorithm in use.

Seam carving was firstly proposed in 2007 [1], and the main purpose of the algorithm is to resize an image while preserving the important image content. By recursively removing a seam, which is a path of pixels with the lowest accumulative energy, the image can be retargeted to a new size and the visual content can be well preserved. A seam can be horizontal or vertical, i.e., crossing the image from left to right, or from top to bottom, and pixels in a seam are all 8-connected. By forcing each row can only have one pixel be included in a vertical seam and each column can only have one pixel be included in a horizontal seam, the rectangular shape of the image can be maintained after seam deletion. Because of its content awareness, seam carving has become one of the most popular image resizing algorithms, and is included as a functionality in many prevalent image editing software, such as Photoshop CS4 and GIMP. Moreover, seam carving can be utilized for image forgery as well, i.e., object removal [1]. Therefore, detecting seam carving has become a hot topic in image forensics, and aroused increasingly attention from scientists.

To detect if seam carving has been applied or not, a few works have been published. In the first work [13], Markov features of DCT coefficient were utilized to detect seam carving in JPEG compressed image. Later, various types of statistical features were proposed to estimate the seam carving in uncompressed or JPEG images [3,4,6,17]. Ryu et al. [12] proposed a set of energy based features which measure the energy bias and noise level of images to detect the trace of seam carving. A patch based approach is later reported by Wei et al. [18]. With the proposed nine types of directional patch operators, local region is rebuilt to nine predictive patches. A patch indexing map is then generated by matching those predictive patches with the proposed reference pattern. Finally, Markov features extracted from the indexing map are applied to detect seam carving. Inspired by Ryu et al. [12], similar features were proposed by Yin et al. [19] however features are extracted from the Local Binary Pattern (LBP) [8] encoded image. The reported results indicate the proposed method outperforms previously published works. Besides of the aforementioned machine learning based passive forensic methods, an active approach was presented by Lu and Wu [7]. The pre-extracted SIFT features are encoded and attached to the image at the sender side, and these side information will be thereafter utilized by the receiver to

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authenticate each received image in order to counter possible seam carving forgery during the transmission.

In this paper, an advanced statistical feature model consisting of local derivative pattern (LDP), Markov transition probability (Markov) and subtractive pixel adjacency model (SPAM) is proposed to detect seam carving applied to uncompressed digital images. The experimental results have illustrated the effectiveness and robustness of proposed feature model. By applying SVM-recursive feature elimination (SVM-RFE), the performance of the proposed feature model is further improved, i.e., with some partially selected features the remarkable performance can be achieved. Besides, the proposed feature model is also applied to reveal seam carving process in JPEG images and geometrical transformed uncompressed images. The experimental results have indicated that the proposed feature model is also reliable on detecting seam carving in JPEG images and robust to geometrical transforms, i.e., image rotation and scaling.

The rest of this paper is organized as follows. In Section 2, seam carving for size reduction is briefly introduced. Then, the proposed approach is presented in Section 3. Experimental results are reported in Section 4. The conclusion is made in Section 5.

2. Background

Traditional image resizing techniques, e.g., scaling and cropping, can successfully manipulate the image size. However, the important image content may not be well preserved. Therefore, seam carving is proposed to solve this problem.

Seam carving, also known as content-aware image resizing, is such a kind of algorithms that aims at reducing image size without destroying the important visual content of the image. Its basic idea is to remove multiple seams with lower cumulative energy cost, which can be considered as ‘less important’ information of the image, from the image to conduct resizing while preserve the image's important content. Each seam is a path consisting of 8-connected pixels crossing the image either from left to right (horizontal seam), or from top to bottom (vertical seam). Moreover, to preserve the rectangle shape of a digital image, a horizontal seam contains only one pixel in each column, and a vertical seam contains only one pixel in each row. For an $n \times m$ image I, the energy of each pixel can be defined as $e(I(x, y))$, where x and y are the row coordinate and column coordinate, respectively, and e is the energy function. A popularly utilized energy function e is based on image gradient as shown below.

$$e(I(x,y)) = \left|\frac{\partial}{\partial x} I(x,y)\right| + \left|\frac{\partial}{\partial y} I(x,y)\right|. \tag{1}$$

For instance, in order to reduce the width of image I, vertical seams which are from top to bottom are to be deleted. Each vertical seam is defined as:

$$s^V = \left\{s_i^V\right\}_{i=1}^{n} = \{(i, y(i))\}_{i=1}^{n}, \ \ s.t. \ \forall i, \ \ |y(i) - y(i-1)| \le 1 \tag{2}$$

where s_i^V is the location of each pixel in the seam and $y(i)$ is the column coordinate corresponding to the pixel in row i. Consequently, each vertical seam is 8-connected and only has one pixel in each row. Assume the cumulative energy for each seam is $E(s)$, then the seam s^* with minimum energy is,

$$s^* = \min_s E(s) = \min_s \sum_{i=1}^{n} e\left(I\left(s_i^V\right)\right) \tag{3}$$

By using dynamic programming, s^* can be determined. The minimum energy M of each pixel (i, j) for all possible connected seams is:

$$\begin{aligned} M(i,j) &= e(i,j) \\ &+ \min\left(M(i-1,j-1), M(i-1,j), M(i-1,j+1)\right) \end{aligned} \tag{4}$$

With the obtained M matrix, the minimum $M(i, j)$ in the bottom row is the end of the target seam. Then, by backward searching, the entire seam could be tracked. Similarly, the horizontal seams could also be determined. Therefore, as shown in Fig. 1, after removing those seams, the image size can be reduced and also the important image content can be preserved. Further, it is difficult to discriminant if an image, which is resized by the seam carving, has been manipulated or not with human eyes.

3. Methodology

As presented in Section 2, seam carving is a good solution for image resizing because of its content awareness. However, image content is inevitably altered due to the missing pixels although the visual impact is very limited or even unnoticeable, and the relation between neighboring pixels is changed as well. Therefore, we present a hybrid feature model which statistically depicts changes made among neighboring pixels so as to reveal the trace of seam carving. In our proposed feature model, each image is represented by a 3058-D feature vector which consists of 2048-D LDP features, 324-D Markov features, and 686-D SPAM features.

LDP is a high-order local descriptor. It encodes the local derivative information with an 8-bit binary pattern. As so, the relation between the central pixel and its eight neighboring pixels depicted by LDP is more complicated than other low-order local descriptors such as LBP. In other words, LDP could also be more sensitive to the manipulation of the local area, including the pixels that are deleted by seam carving.

Both Markov transition probability, denoted as Markov features, and subtractive pixel adjacency model, denoted as SPAM features, are transition probability based. The difference between Markov features and SPAM features is mainly on the order, because Markov feature depicts the relation between two adjacent pixels while SPAM feature normally represents the relation between three or more consecutive adjacent pixels. As the pixels with lower energy may be deleted by seam carving, the distribution of pixel values will be changed too and so as the transition probability. Therefore, Markov features and SPAM features could also be sensitive to the seam carving process.

In summary, all of these three types of features can capture the changed relation between neighboring pixels, and it is believed that the combination could be more discriminative. Thus, we proposed this advanced hybrid feature model for the seam carving detection. To further improve the performance of the proposed feature model, SVM-recursive feature elimination has been employed for feature selection. In what follows, the proposed advanced statistical feature model and the feature selection scheme are introduced in detail.

3.1. LDP features

As a local descriptor, LDP [20] can be considered as a directional high order derivative binary pattern comparing with LBP which can be considered as the 1st order non-directional descriptor. It captures more discriminate information from the derivative perspective, and more sensitive to the changes of the local region. As shown in Fig. 2, for a given local 5×5 block with the central pixel at Z_0 in image I, the 1st order derivative of pixel Z_0 in I along the 4 directions, $\alpha = 0^\circ, 45^\circ, 90^\circ$ and 135° can be derived as following

$$\begin{aligned} I'_{\alpha=0^\circ}(Z_0) &= I(Z_0) - I(Z_4), \\ I'_{\alpha=45^\circ}(Z_0) &= I(Z_0) - I(Z_3), \\ I'_{\alpha=90^\circ}(Z_0) &= I(Z_0) - I(Z_2), \\ I'_{\alpha=135^\circ}(Z_0) &= I(Z_0) - I(Z_1) \end{aligned} \tag{5}$$

where $I(Z)$ is the intensity of pixel Z. Considering pixels $\{Z_i | i = 1 \ldots 8\}$ which are adjacent to Z_0 with a distance equal to 1 pixel, the 2nd