2010 International Conference on Multimedia Information Networking and Security

Image Copy-move Forgery Detection Based on SURF

Xu Bo, Wang Junwen, Liu Guangjie and Dai Yuewei
School of Automation
Nanjing University of Science & Technology
Nanjing 210094, China
xubo.njust@gmail.com

***Abstract*—As the advent and growing popularity of image editing software, digital images can be manipulated easily without leaving obvious visual clues. If the tampered images are abused, it may lead to potential social, legal or private consequences. To this end, it's very necessary and also challenging to find effective methods to detect digital image forgeries. In this paper, a fast method to detect image copy-move forgery is proposed based on the SURF (Speed up Robust Features) descriptors, which are invariant to rotation, scaling etc. Results of experiments indicate that the proposed method is valid in detecting the image region duplication and quite robust to additive noise and blurring.**

Keywords- copy-move; SURF; image forensics

I. INTRODUCTION

Image editing software is becoming more and more sophisticated and powerful. Digital images can be edited easily, without leaving obvious visual clues. A consequence of problems will occur in applications such as criminal investigation, mass media, and so on, concerning the authentic of digital images. Hence, images an important issue in forensic science.

Digital multimedia forensic verify the authenticity and origin of multimedia files independent of any previously embed information or fingerprint. Compared to the active authentic techniques, such as digital watermarking and digital fingerprint, digital forensic can be applied to multimedia data without additional information. As a result, the research of digital multimedia forensic has drawn a lot of attentions recently. [1-3]

Copy-move is a specific type of image forgery, where a part of the image is copied and pasted on another part of the same image. One direct approach to this problem is proposed by Fridrich et al. [4]. They performs an exhaustive search by comparing the image to every cyclic-shifted versions of itself, which requires $(MN)^2$ steps for an image sized M by N. They also proposed to use the autocorrelation properties of the image to detect the duplicated regions. Another approach to detect copy-move forgeries is the block-matching method, which divides the image into overlapping blocks. This approach tries to detect connected image blocks that were duplicated.

One of the challenges of copy-move forensic is to find the robust features of the image blocks. Fridrich et al. [4] use DCT coefficients, which are robust to low-pass filtering and compression. Popescu et al. [5] use principal component analysis, which were also robust to additive Gaussian noise and JPEG compression. Similarly, Li et al. [6] extracted features by applying SVD to low frequency wavelet bands. Another challenge of copy-move forensic is to detect the duplicated blocks within a relatively low time complexity. Lexico-graphically sort is employed to sort the feature vectors, so that blocks with similar features would follow each other.

A robust image copy-move detection method is proposed. The fast and robust SURF keypoints are employed to find the possible duplicate regions in the image. The rest of the paper is organized as follows. In the next section, the SURF algorithm is introduced and the feature extraction and matching method is described. Experiment and result analysis is presented in section 3. Finally, a conclusion is given in the last section.

II. SURF

A. SURF keypoints generation

SURF (Speeded Up Robust Features) has been recently published by Bay et al. [7]. The SURF approach describes a keypoint detector and descriptor. Keypoints are found by using a so called Fast-Hessian Detector that bases on an approximation of the Hessian matrix for a given image point. The responses to Haar wavelets are used for orientation assignment, before the keypoint descriptor is formed from the wavelet responses in a certain surrounding of the keypoint.

B. Fast Interest Point Detection

The SURF feature detector is based on the Hessian matrix. Given a point x =(x, y) in an image I, the Hessian matrix H(x, σ) in x at scale σ is defined as follows

$$\mathrm{H}(x,\sigma)=\begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix}, \tag{1}$$

where $L_{xx}(x,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image I in point x, and similarly for $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$.

978-0-7695-4258-4/10 $26.00 © 2010 IEEE
DOI 10.1109/MINES.2010.189

In contrast to SIFT, which approximates Laplacian of Gaussian (LoG) with Difference of Gaussians (DoG), SURF approximates second order Gaussian derivatives with box filters. Image convolutions with these box filters can be computed rapidly by using integral images. The entry of an integral image $I_\Sigma(x)$ at location $x = (x, y)^T$ represents the sum of all pixels in the base image I of a rectangular region formed by the origin and x.

Once we have computed the integral image, it is strait forward to calculate the sum of the intensities of pixels over any upright, rectangular area. The location and scale of interest points are selected by relying on the determinant of the Hessian. Hereby, the approximation of the second order derivatives is denoted as D_{xx} , D_{yy} , and D_{xy} . By choosing the weights for the box filters adequately, an approximation for the Hessian's determinant is found

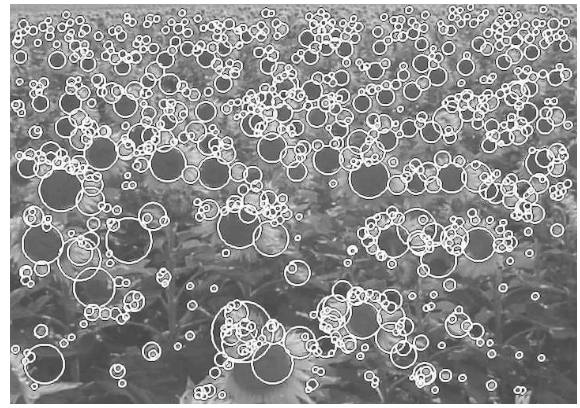
$$\det(H_{approx}) = D_{xx}D_{yy} - (0.9D_{xy})^2 \quad (2)$$

Interest points are localized in scale and image space by applying non-maximum suppression in a 3 × 3 × 3 neighborhood. Finally, the found maxima of the determinant of the approximated Hessian matrix are interpolated in scale and image space.

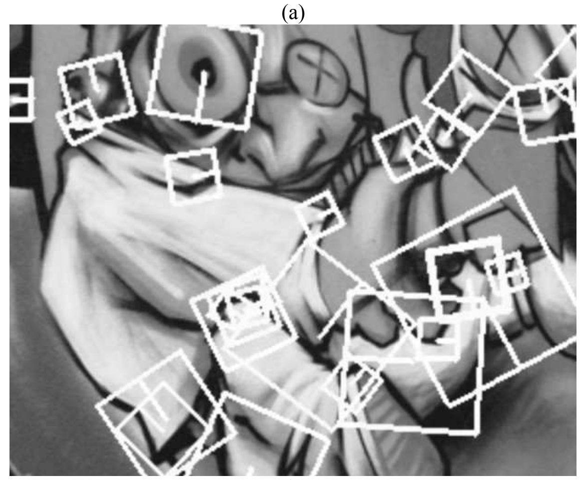
C. Interest Point Descriptor

In a first step, SURF constructs a circular region around the detected interest points in order to assign a unique orientation to the former and thus gain invariance to image rotations. The orientation is computed using Haar wavelet responses in both x and y direction as shown in Fig. 1. The Haar wavelets can be easily computed via integral images, similar to the Gaussian second order approximated box filters. Once the Haar wavelet responses are computed, they are weighted with a Gaussian with σ = 2.5s centered at the interest points. In a next step the dominant orientation is estimated by summing the horizontal and vertical wavelet responses within a rotating wedge, covering an angle of π/3 in the wavelet response space. The resulting maximum is then chosen to describe the orientation of the interest point descriptor.

In a second step, the SURF descriptors are constructed by extracting square regions around the interest points. These are oriented in the directions assigned in the previous step. The windows are split up in 4 by 4 sub-regions in order to retain some spatial information. In each sub-region, Haar wavelets are extracted at regularly spaced sample points. In order to increase robustness to geometric deformations and localization errors, the responses of the Haar wavelets are weighted with a Gaussian, centered at the interest point. Finally, the wavelet responses in horizontal d_x and vertical



(a)



(b)

Figure 1. (a): Detected interest points for a Sunflower field. This kind of scenes show clearly the nature of the features obtained from Hessian-based detectors. (B): Detail of the Graffiti scene showing the size of the descriptor window at different scales.

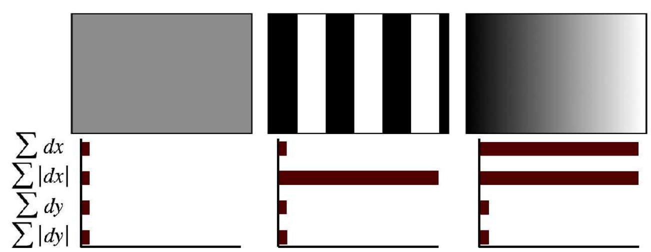


Figure 2. The descriptor entries of a sub-region represent the nature of the underlying intensity pattern. Left: In case of a homogeneous region, all values are relatively low. Middle: In presence of frequencies in x-direction, the value of $\sum |d_x|$ is high, but all oPthers remain low. If the intensity is gradually increasing in x-direction, both values $\sum d_x$ and $\sum |d_x|$ are high..

Directions d_y are summed up over each subregion. Furthermore, the absolute values $|d_x|$ and $|d_y|$ are summed in order to obtain information about the polarity of the image intensity changes. Hence, the underlying intensity pattern of each sub-region is described by a vector

$$\mathbf{v} = (\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|) . \quad (3)$$

The resulting descriptor vector for all 4 by 4 sub-regions is of length 64. See Fig. 2 for an illustration of the SURF descriptor for three different image intensity patterns. Notice that the Haar wavelets are invariant to illumination bias and additional invariance to contrast is achieved by normalizing the descriptor vector to unit length.

D. SURF feature descriptors matching

Keypoints match is done between two images typically. Given a pair of images $\mathbf{I_i}, \mathbf{I_j}$ with their respective interest points and feature descriptors, for every interest point in the first image Ii, we calculate the Euclidian distance to all feature descriptors in the second image $\mathbf{I_i}$. If the ratio of the nearest neighbor and the second-nearest neighbor is smaller than a predefined threshold, which is discussed in the experiment, a match is assumed to be correct and is therefore added to the list of putative matches. In our paper, the match process of keypoints is done by matching between two subsets of the keypoints set of the test image, as described in follows.

(1) Given a keypoints set of test image as S, randomly divide the set into two subsets as S_1, $S_2, S_1 \cup S_2 = S$.

(2) Find the nearest neighbors in S_1, S_2, and save the matching records.

(3) Applying step (1), (2) to S_1, S_2 respectively and repeatedly until S_1, S_2 only contains one element.

By using the above matching method, the keypoints matches can be found, and the duplication can be further determined.

III. EXPERIMENT

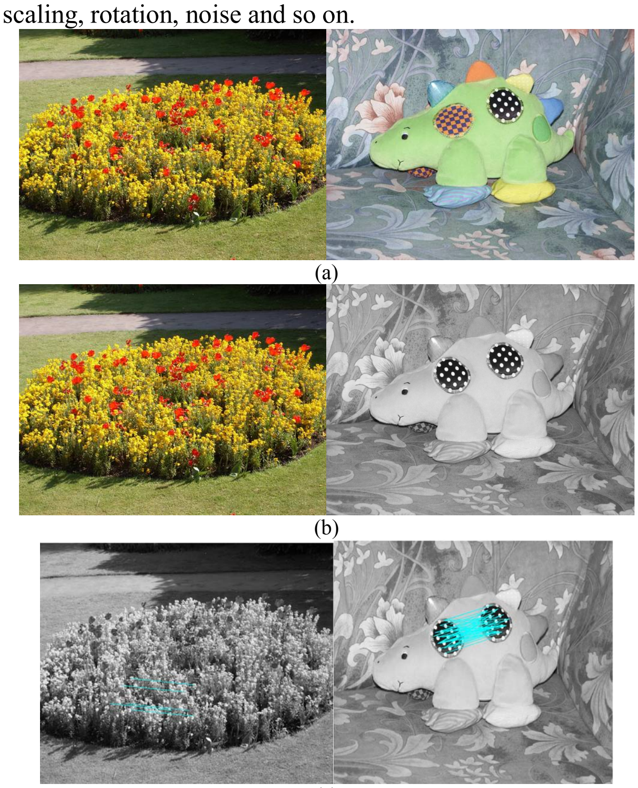
A. Experiment Setup

The SURF algorithm implemented by Herbert Bay et al. is used to detect the keypoints and get the descriptors. The experiment environment is as follows, the operation system is based on the Linux-2.6.32-22 kernel, GCC 4, 64 bit. In the experiment, we use the extended descriptor mode to get the 128d SURF descriptors. The test images are chosen from the UCID: Uncompressed Color Images Database, and edited using the GIMP software.

B. Experiment Results and Analysis

As shown in Fig. 3 (a) are the original images 'Flowers' and 'Toy' , (b) are the faked images of copy-move forgery. In the former one the flowering shrubs on the bottom was copied and pasted on its right side, and in the latter one the dotted region was copied and moved onto the squared texture region. The proposed detection method is used to detect duplicate regions in them. SURF keypoints features are extracted by first, and their descriptors are matched within each other with a threshold ω. A larger threshold means more match points, thus tends to come with more false matches, while a smaller one will get more accurate matches with less match points. In this paper, it is empirically set to be 0.35, within all the test images, to strike a balance between numbers of correct matches and total numbers of matches. The detection results are displayed in the image with lines between two matched keypoints. By observing the detection results, the duplication regions can be figured out.

The robustness of the proposed method to scaling, rotation, blurring and noise are further tested. Images are copied and pasted with operations such as, scaling, rotation, blurring and additive noise. In Fig. 4 and Fig. 5, the tampered images and detection results can be found. The parameters of these operations are as follows: the rotation angle in Fig. 3(a) and Fig. 4 are 55 degree anti-clockwise, the scaling factors in Fig. 4(a) and Fig. 5 are 1.15, 1.05 respectively, the blur radius is 1,1 and the blur method is the default option, the Gaussian noise are added to get the SNR of 24. We can find the proposed method can reliably detect the duplicated regions, and can stand the operations of scaling, rotation, noise and so on.

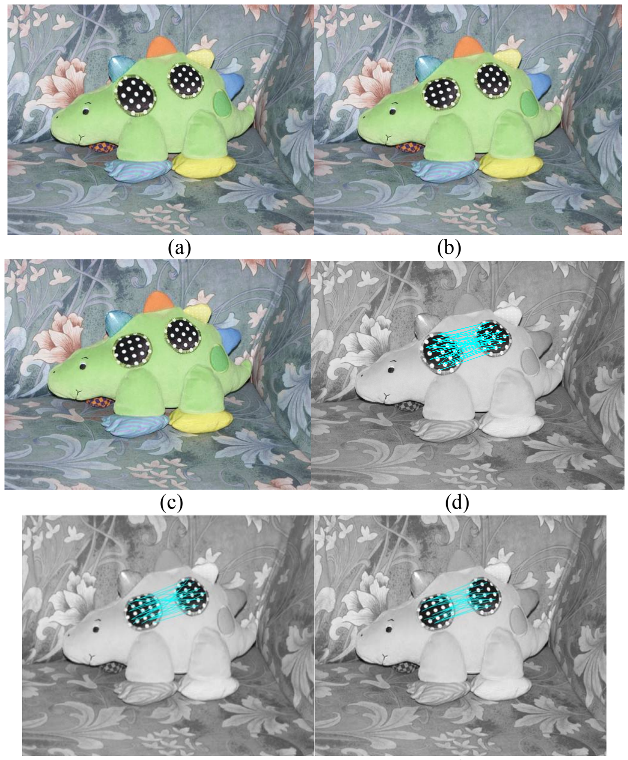


(a)

(b)

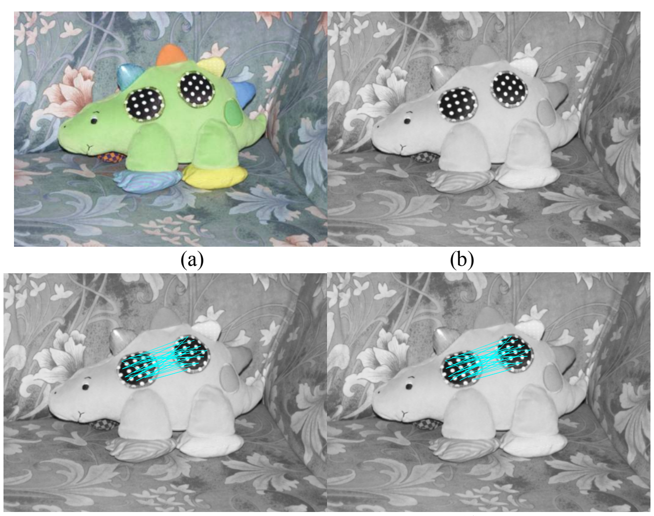
(c)

Figure 3. Test images of copy-move and their detection results: (a) Original images 'Flowers' and 'Toy', (b) Images of copy-move forgery. (c) Detection results of copy-move forgery.



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

Figure 4. Detection results of copy-move forgery with scaling and rotation: (a) Image copy-move forgery with scaling, (b) rotation, (c) scaling and rotation, (d), (e), (f) detction results of (a) and (b) and (c).



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

Figure 5. Detection results of copy-move forgery with post processing:(a) Image copy-move forgery with scaling, rotation and blurring, (b) Image copy-move forgery with scaling, rotation and noise, (c) (d) detction results of (a) and (b).

IV. Conclusion

A fast yet robust method to detect image copy-move forgery is proposed. Detecting and extracting the robust SURF interest points and their descriptors by first, the possible duplicated regions in test images can be found by matching the descriptors vectors. Experiment result indicate that this method can detect the copy-move forgery quickly, and can stand certain transformations and post processing such as, scaling, rotation, noise blurring and so on. However, further investigation is still needed to automatic locate the tampered region and its boundary.

References

.

[1] T. V. Lanh; K.-S. Chong; S. Emmanuel.; M.S. Kankanhalli, A Survey on Digital Camera Image Forensic Methods, IEEE International Conference on Multimedia and Expo (ICME'07), Beijing, pp.16-19, July, 2007.

[2] H. T. Sencar, and N. Memon, Overview of State-of-the-art in Digital Image Forensics, Statistical Science and Interdisciplinary Research, World Scientific Press, 2008.

[3] J. Fridrich, Digital Image Forensic, IEEE Signal Processing Magazine, vol. 26, Issue 2,pp. 26-37, March 2009.

[4] J. Fridrich, D. Soukal, and J. Lukas, Detection of copy-move forgery in digital images, Proc. Digital Forensic Research Workshop, Cleveland, OH, August 2003.

[5] A.C. Popescu and H. Farid, Exposing digital forgeries by detecting duplicated image regions, Technical Report, TR2004-515, Dartmouth College, Computer Science, 2004.

[6] Guohui Li, Qiong Wu, Dan Tu, and ShaoJie Sun, A sorted neighborhood approach for detecting duplicated regions in image forgeries based on dwt and svd, ICME, 2007.

[7] Herbert Bay, Andreas Ess, Tinne Tuytelaars, Luc Van Gool, SURF: Speeded Up Robust Features, Computer Vision and Image Understanding (CVIU), Vol. 110, No. 3, pp. 346-359, 2008.