

## A Novel Approach for Detection of Copy-Move Forgery

Mengyu Qiao<sup>1</sup>, Andrew H. Sung<sup>2</sup>, Qingzhong Liu<sup>3</sup>, Bernardete M. Ribeiro<sup>4</sup>

<sup>1</sup>Dept. of Math and Computer Science, South Dakota School of Mines and Technology, mengyu.qiao@sdsmt.edu

<sup>2</sup>Dept. of Computer Science and Engineering, New Mexico Tech, sung@cs.nmt.edu

<sup>3</sup>Dept. of Computer Science, Sam Houston State University, qxl005@shsu.edu

<sup>4</sup>Dept. of Informatics Engineering, University of Coimbra, bribeiro@dei.uc.pt

**Abstract**—With the increasing popularity of digital media and the ubiquitous availability of media editing software, innocuous multimedia are easily tampered for malicious purposes. Copy-move forgery is one important category of image forgery, in which a part of an image is duplicated, and substitutes another part of the same image at a different location. Therefore, it is necessary to have reliable and efficient methods to detect copy-move forgery for applications in law enforcement, forensics, etc. In this paper, based on multi-resolution and multi-orientation curvelet transform, we propose a blind forensics approach for the detection of copy-move forgery. In detail, the input image is segmented into overlapping blocks, and then curvelet transform is applied to each block. Statistics of curvelet sub-bands are extracted and sorted. Finally, duplicated blocks are identified by comparing their similarity. The proposed approach intends to reduce the complexity, improve the accuracy of the detection, and potentially resist shifting manipulation.

**Keywords**—Copy-Move Forgery; Image Forensics; Curvelet Transform

### I. INTRODUCTION

With the development of high-definition acquisition equipment, large capacity storage device, and high speed network, multimedia applications have become increasingly popular in our daily life. At the same time, the imperceptible manipulation of digital media for malicious purpose has been simplified by the pervasive availability of media editing software. While we are undoubtedly exposed to huge volume of digital media, our traditional confidence in the integrity of these media has also been eroded since doctored pictures, video clips, and voices are appearing with a growing frequency and sophistication in mainstream media outlets, scientific journals, political campaigns, and courtrooms [1].

In order to protect the integrity and reveal the manipulation of digital media, two types of countermeasures, proactive approach and reactive approach, are extensively investigated in previous studies. Proactive approach, including digital signature, watermarking, and etc., relies on preprocessing before distribution, which requires additional and shared information. However, there is no universally recognized standard, and the complexity greatly restricts its application. On the other hand, the reactive approach only requires digital media without any supplemental information. Due to the variety of manipulations and the diversity of individual characteristics of media, reactive approach usually

faces difficulties at a larger scope, and suffers from complicated and time-consuming problems.

Copy-move forgery is conducted by duplicating a part of targeted image and substituting another part of the same image to increase the occurrences of certain objects, or conceal an important region. As one of the major categories of image forgery, copy-move manipulation has its unique characteristic – the source and the destination of the duplicated parts are in the same image, so the noise patterns are similar to those from surrounding regions. This important characteristic invalids the application of methods for detecting other types of tampering, such as splicing, double compression, etc. [2, 3, 4, 5]. Figure 1 illustrates an example of copy-move forgery, where the original image (a) has four different original pictures and the tampered one (b) contains an additional picture.

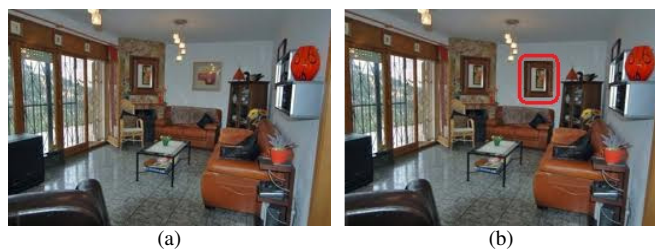


Figure 1. Example of Copy-Move forgery original image (a) and tampered image (b).

In recent years, multiple detection methods have been proposed to address copy-move forgery. As one of the common analysis of image forensics, moment statistics has been successfully applied for detecting a variety of tampering, including splicing, double compression, steganography, and etc. Mahdian and Saic proposed blur-invariant moments as features for detection [6]. Wang et al. presented first four Hu-moments for detection [7]. To reduce the dimensionality and improve efficiency, principal component analysis (PCA) [8] and singular value decomposition (SVD) [9] were applied to obtain reduced feature space. Features from other transform domains, such as discrete wavelet transform (DWT) [10] and Fourier-Mellin transform (FMT) [11] were proposed as alternative detectors.

To detect copy-move forgery, in this paper, we propose an approach based on multi-resolution and multi-orientation curvelet transform. Statistical features are extracted from curvelet sub-bands of overlapping blocks, and reduced

features are generated for similarity measure. Restrictive criteria are defined to suppress false-positive. Compared to exhaustive search in spatial domain, the proposed approach intends to reduce the complexity, improve the accuracy of the detection, and potentially resist shifting manipulation. The remainder of this paper is organized in this way: Section II introduces the curvelet transform, while Section III presents the proposed approach for detecting copy-move forgery. The experiments and results are described in Section IV. Conclusions are made in Section V.

## II. INTRODUCTION TO CURVELET TRANSFORM

The concept of wavelet transform was developed to represent both location and spatial frequency in 1D signal. For 2D signal, like digital image, curvelet transform provides directional information at different scales. The definition of curvelet transform is derived from 2D ridgelet transform at multiple scales. If an image is denoted as  $f(x,y)$ , then the continuous ridgelet coefficients are described as [12]:

$$\mathfrak{R}_f(a,b,\theta) = \iint \psi_{a,b,\theta}(x,y) f(x,y) dx dy \quad (1)$$

where  $a$  is the scale parameter and  $a > 0$ ,  $b \in \mathbb{R}$  is the translation parameter, and  $\theta \in [0, 2\pi)$  is the orientation parameter. A ridgelet can be defined as [12]:

$$\psi_{a,b,\theta}(x,y) = a^{-\frac{1}{2}} \psi\left(\frac{x \cos \theta + y \sin \theta - b}{a}\right) \quad (2)$$

where  $\theta$  is the orientation of the ridgelet. Ridgelets are constant along the lines  $x \cos \theta + y \sin \theta = const$  [12].

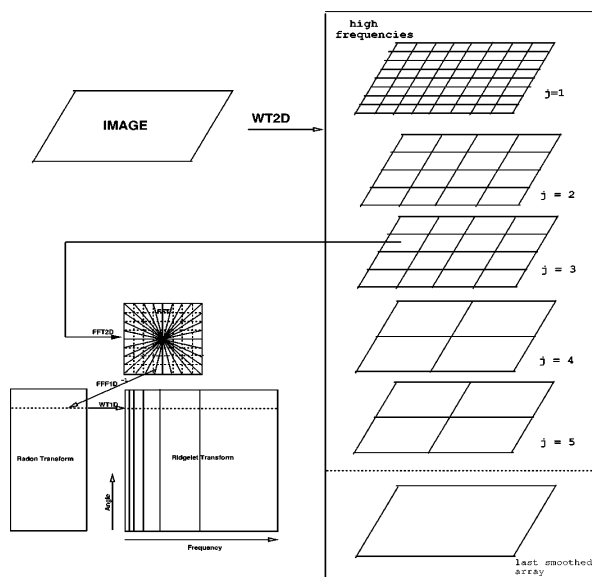
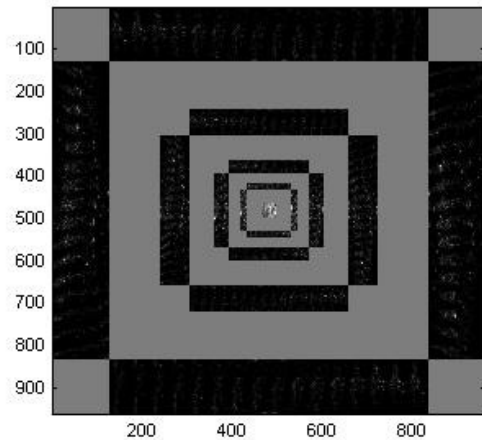


Figure 2. An overview of discrete curvelet transform.

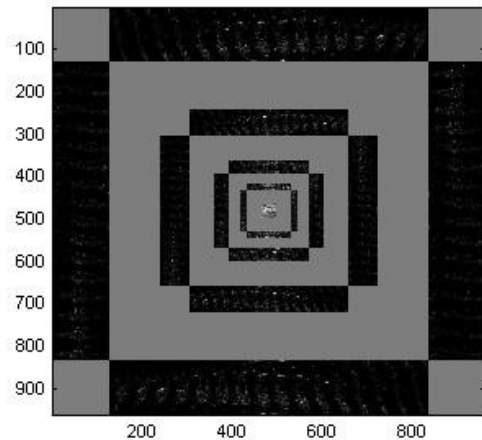
In curvelet transform, an input image is decomposed into a set of sub-bands, and each sub-band is then partitioned into several blocks for ridgelet analysis. The ridgelet transform is applied by combining the Radon transform and the 1-D

wavelet transform [12]. To achieve higher level of efficiency, curvelet transform is usually implemented in the frequency domain.

Figure 2 shows an overview of discrete curvelet transform, which generates a group of coefficient matrices in different scales and orientations [12].



(a)



(b)

Figure 3. Curvelet transform of original (a) and 90 degree rotated (b) images generated by using Curvelab-2.1.2 [14].

Since complex ridgelet transform has higher computational complexity, fast discrete curvelet transform is implemented by wrapping of Fourier samples [13]. The pyramid structure of curvelet transform generates multiple orientations at various scales, which greatly benefits the identification of duplicated regions in both accuracy and robustness. Multi-directional decomposition provides a more precise approximation of the relation between adjacent orientations, and further supports the tolerance of rotation and shifting manipulations. Figure 3 shows the curvelet transform of original (a) and 90 degree rotated (b) images, which are generated by using Curvelab-2.1.2 [14]. It is clearly illustrated that all curvelet coefficients rotate with the rotation of the image simultaneously. Therefore, the pattern

of individual orientation is preserved, and the transitions of adjacent orientations remain. This important property leaves us clue to improve copy-move forgery detection.

### III. DETECTION METHOD

Inspired by the observation of multi-directional curvelet transform, we design an analytical approach to detect duplicated regions based on statistics of curvelet coefficients.

#### A. Structure of Approach

The proposed approach consists of two phases. In the first phase, the overlapping blocks of a source image are sorted according to statistics of multiple curvelet sub-bands. The detailed procedure of the first phase is described in Figure 4.

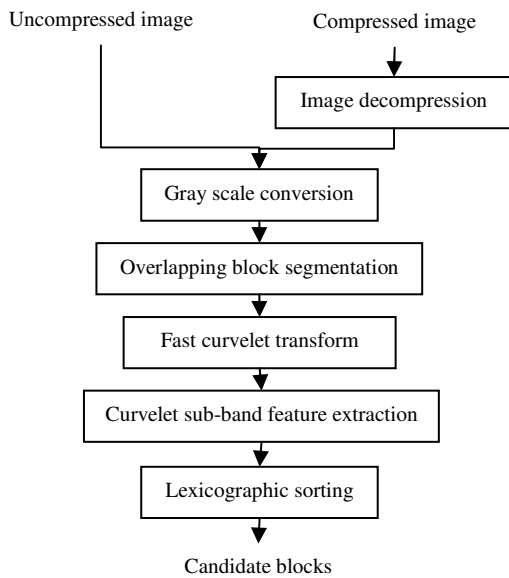


Figure 4. The structure of the first phase.

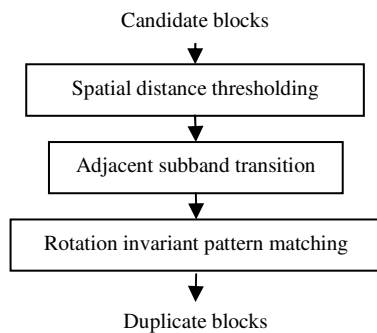


Figure 5. The structure of the second phase.

In the second phase, the number of candidate block pairs has been dramatically reduced, and the spatial distance between each pair of blocks is considered to reduce the false-positive of similar blocks from same object or texture.

Orientation related block features are extracted for pattern matching. Considering relation between adjacent orientations, the rotation or shifting effects could be minimized. The procedure of the second phase is illustrated in Figure 5.

#### B. Curvelet Sub-Band Feature Extraction

In order to extract statistical features, the gray scale image is segmented into a series of overlapping blocks. Then, we apply fast curvelet transform to individual blocks. Given a block  $B[i,j]$  of dimension  $N$  by  $N$ , the curvelet transform could be obtained from:

$$CT(a,b,\theta) = IFFT\left(FFT(B[i,j]) \times FFT(\psi_{a,b,\theta}[i,j])\right) \quad (3)$$

According to the setting of block size  $N$ , each block is decomposed into 3 or 4 levels of scales. Different scales consist of various numbers of sub-bands. For 3 levels decomposition, the level 1, 2 and 3 include 1, 16, and 1 sub-bands respectively. We define the sub-band of curvelet transform as  $ct$ , so the 3 levels curvelet coefficients are denoted as:

$$CT = \left\{ (ct_{1,1}), (ct_{2,1}, ct_{2,2}, \dots, ct_{2,16}), (ct_{3,1}) \right\} \quad (4)$$

In order to reduce the feature dimension and resist rotation manipulation, we compute the mean values of each sub-band, and sort those in same level of scale. In 3 levels decomposition, the level 1 and 3 contain only one sub-band, so there is no further processing. Level 2 consists of 16 sub-bands, and the mean values of those are denoted as follows:

$$M_{CT\{2\}} = m_1, m_2, \dots, m_{16} \quad (5)$$

The sorted features of 3 levels decomposition could be obtained as

$$M_{CT} = \left\{ M_{CT\{1\}}, M'_{CT\{2\}}, M_{CT\{3\}} \right\} \quad (6)$$

$M_{CT}$  will be used for lexicographic sorting. Then adjacent pairs of blocks in the rank could be provided to the second phase as candidate blocks.

#### C. Adjacent Sub-band Transition

In the rotation manipulation, all the sub-bands of ordinations shift at the same degree, thus the relation between adjacent sub-bands basically remains. Although the absolute values might vary, the distributions of transitions are very similar to the original ones regardless of shifting. Therefore, we obtain the differences between each adjacent pair of sub-bands in level 2 by:

$$D(i) = \left| m_i - m_{\text{mod}((i+1),16)} \right|, i = 1, 2, \dots, 16 \quad (7)$$

#### D. Rotation Invariant Pattern Matching

In order to minimize the directions of the candidate blocks, we sort the difference vector and use the sorted vector as a rotation invariant descriptor of each candidate

block. For each similar pair of blocks, we compute Euclidean distance between their descriptors as similarity measure. For 3 levels decomposition, the descriptor of level 2 sub-bands is used for similarity measure. The similarity between a pair of blocks  $p$  and  $q$  is obtained from:

$$S(p, q) = \sqrt{\sum_{i=1}^{16} |D_p(i) - D_q(i)|^2} \quad (8)$$

Considering small distortion introduced by rotation, compression, or noise adding, a selected threshold is set to determine duplicated blocks. For different resolutions of image and different levels of decomposition, the threshold should be adjusted accordingly.

#### IV. EXPERIMENTS AND RESULTS

The original 100 raw images were obtained in never compressed format used in our previous study of steganalysis [15]. We created copy-move forgery with various sizes of duplicated regions. Then the doctored images were compressed into JPEG format at quality factor of 90. Different parameter settings, which include block size and similarity threshold value, were tested to enhance the detection performance.

Figure 6 illustrates two copy-move forgery images and their identified masks with the duplicated regions. Table I shows the statistics of the detection results, which indicates good detection accuracy and stable detection performance.

TABLE I. DETECTION RESULTS OF 100 COPY-MOVE IMAGES

Average Precision	Maximum Precision	Minimum Precision	Standard Deviation of Precision
97.88%	100.00%	90.09%	0.024

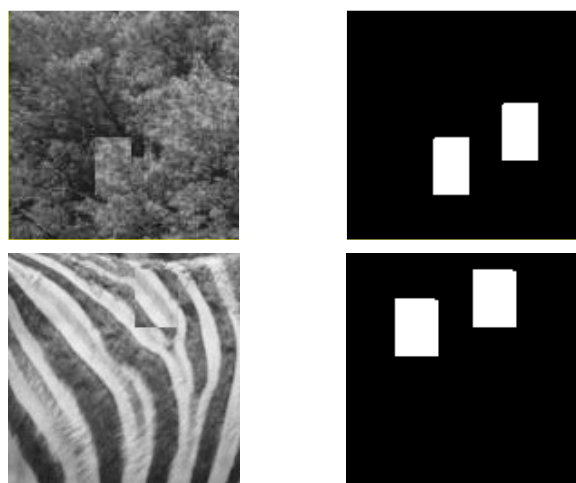


Figure 6. The copy-move forgeies and the identified duplicated regions.

#### V. CONCLUSIONS

In this paper, based on multi-resolution and multi-orientation curvelet transform, we presented an approach for detecting copy-move forgery of duplicated regions within

same image. Curvelet sub-band features effectively represent properties of individual region, and efficiently identify duplicated blocks. Experimental results show that the proposed approach obtains good performance in detecting duplicated regions even after JPEG compression. Moreover, this approach also preserves good potential in identifying rotation and scale manipulations in addition to the basic copy-move forgery.

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