Digital Image Forensics Using Multi-Resolution Histograms

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ABSTRACT

In this paper, the authors investigate the prospect of using multi-resolution histograms (MRH) in conjunction with digital image forensics, particularly in the detection of two kinds of copy-move manipulations, i.e., cloning and splicing. To the best of the authors’ knowledge, this is the first work that uses the same feature in both cloning and splicing forensics. The experimental results show the simplicity and efficiency of using MRH for the purpose of clone detection and splicing detection.

Keywords: Copy-Move Manipulations, Digital Image Blind Forensic, Image Clone Detection, Image Splicing Detection, Multi-Resolution Histogram

INTRODUCTION

With the development of digital image processing technology, and wide spread use of digital image processing software, such as Photoshop, the modification of digital images has become much easier for people without professional knowledge. This makes our lives more colorful; however, a new problem is introduced. Is a digital image’s authenticity trustworthy? How do we check the digital image’s authenticity? Therefore, using digital image forensics to check a digital image’s authenticity has become a significant research focus. We will review the current digital image forensics technology first.

INTRODUCTION TO DIGITAL IMAGE FORENSICS

To acquire a forged image, we first shoot a scene to get the original image with a camera, and then alter the image with different types of manipulation technologies. On one hand, during photographing process, the camera itself may introduce some distinct artifacts into an image because of its image processing mechanism. On the other hand, the manipulation technologies may introduce some distinct artifacts into the
image. These two scenarios are both used in digital image forensics. We can divide current digital image forensics technologies into two classes, one is based on the camera’s photographing mechanism, and the other is based on manipulation methods. The prior one uses camera artifacts introduced by different stages of image processing as evidence to detect manipulation: such as chromatic aberration introduced by an optical system (Micah, Johnson, & Farid, 2006), pixel’s statistical correlations introduced by color filter array interpolation (Popescu & Farid, 2005; Swaminathan & Liu, 2006; Long & Huang, 2006), camera response function with camera sensors (Hsu & Chang, 2006; Lin, Wang, Tang, & Shum, 2005), and sensor noise introduced by whole processing steps (Chen, Fridrich, Luka, & Goljan, 2007; Gou, Swaminathan, & Wu, 2007; Lukas, Fridrich, & Goljan, 2006). Furthermore, there are a wide variety of manipulation methods, therefore, digital image forensic technologies which aim at manipulation methods are varied, such as resampling detection (Gallagher, 2005; Popescu & Farid, 2005; Mahdian & Saic, 2008; Kirchner, 2008; Prasad & Ramakrishnan, 2006) and blur detection (Hsiao & Pei, 2005; Sutcu, Coskun, Sencar, & Memon, 2007). While the forensic method proposed in (Lyu & Farid, 2005; Tian-Tsong, Shih-Fu, Jessie, Lexing, & Mao-Pei, 2005) focus on how to distinguish a naturally occurred image from one computer-generated image.

In our opinion, the most general methods for tampering with an image include two kinds of copy-move manipulation: one is copying and moving a part to a different location within the same image, known as the clone operation; another is copying and moving a part of an image to another separate image, known as splicing. The examples of cloning and splicing are shown in Figure 1. Both of these two operations can easily misguide people’s understanding about the content of the image. For example, in Figure 1 (c), (d), people may be confused as to the original environment within which the cheetah was present.

The initial thought to detect the clone operation is an exhaustive search (Fridrich, Soukal, & Lukas, 2003), as there are two or more completely identical parts within the same image. However, an exhaustive search is less practical, because it is computationally impossible. Therefore many kinds of methods to improve the computational efficiency have been studied in Huang, Guo, and Zhang (2008), Li, Wu, Tu, and Sun (2007), and Popescu and Farid (2004). Most of these methods divide the image into numbers of overlay blocks, extract appropriate representation for each block, then sort and group the blocks to detect a clone region. Li et al. (2007) features of each block are extracted by applying singular value decomposition (SVD) to low frequency wavelet transform bands on each block. In Huang et al. (2008), SIFT features are extracted as representations for each block.

Obviously, the method of clone detection is inadequate for splicing detection because splicing uses separate images. Unless we know the original images that were used to create the composite image, an exhaust search is impossible. Recently, extensive work has been done on splicing detection. Parts of the work extract features from the image, and then perform classification with a classifier. The main difference is that many different features and classifiers are employed. In Ng, Chang, and Sun (2004), bi-coherence features are used to train a SVM to make the classification. In Zhang, Kang, and Ren (2008), moment features and selected Image Quality Metrics (IQMs) are used as features and trained by SVM to classify authentic and spliced images. In Zhen, Yukun, and Xijian (2008) of theirs, the classifier is an Artificial Neural Network. In Lu, Sun, Huang, and Lu, (2008), the authors use higher order statistical features and an RBF neural network to classify the fake and real images. In Hsu and Chang (2006), geometry invariants and camera characteristics consistency are used to detect image splicing. While in Zhang et al. (2008), the authors achieved 85% and above accuracy which is the best result among similar meth-
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