Neurocomputing 207 (2016) 131–140

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Source camera identification from image texture features ☆

Bingchao Xu, Xiaofeng Wang *, Xiaorui Zhou, Jianghuan Xi, Shangping Wang

Xi'an University of Technology, Xi'an, Shaanxi 710048, PR China

ARTICLE INFO

Article history:
Received 15 June 2015
Received in revised form
5 April 2016
Accepted 3 May 2016
Communicated by Dr Zhang Zhaoxiang
Available online 11 May 2016

Keywords:
Source camera identification
Local Binary Pattern (LBP)
Local Phase Quantization (LPQ)
Support vector machine (SVM)

ABSTRACT

Source camera identification enables forensic investigator to discover the probable source model that are employed to acquire the image under investigation. It is important whenever digital content is presented as a silent witness. In this paper, we present a source camera identification method via image texture features that are extracted from well selected color model and color channel. Except to distinguish source camera models from images whatever they are captured via same or different brand cameras, the main contributions of the proposed method are as follows: (1) It can distinguish imaging device individuals from images even if they are taken by using same brand and model of devices. (2) It is robust for content-preserving manipulations or geometric distortions, such as JEPG compression, adding noise, and rotation and scaling. The experimental results demonstrate that the performance of the proposed method is satisfactory. Compared with the state-of-the-art methods, the proposed method is superior in both detection accuracy and robustness.

1. Introduction

With the development of digital technology, digital images can be obtained when and where via various cameras and mobile phones. At the same time, digital image forensics technology has received considerable attention because it can be used to image source identification, image forgery detection, and image operation history tracking. As one of the important branches of the digital image forensics, image source identification has become a hot topic in academia and industrial community. It has widespread applications in many fields, such as judicial system, criminal investigation, news media, and military image identification.

Digital image source identification is a kind of technology that identify image source only from image itself without any information about image generation equipment. It is achieved by using signal processing method. Image source identification depends on the following assumptions: all images acquired from the same imaging device carry same internal characteristics of imaging device, include pattern noise, lens distortion, and Color Filter Array (CFA) mode, these internal characteristics are only related to imaging device, and are irrelevant to scene content. Image source identification includes several aspects:

1) The imaging device identification: identifying the source of a given image as one of the following equipments: digital cameras, printers, scanners, mobile phones and computers.
2) The imaging device brand identification: identifying the brand of imaging device by which the image come from, if one knows the image is captured by a specific imaging device, such as a camera.
3) The imaging device individual identification: identifying certain device individual by which the image is taken, if one knows the image is captured by a specific brand of equipment, such as Sony camera.

1.1. Related work

Taking a general survey on digital image source identification technology, most of the existing works focused on the imaging device brand identification, and there are few of works pay attention to the imaging device individual identification. For the former, the main methods in literature can be divided into three categories: the identification methods based on the characteristics of sensor pattern noise (SPN), the identification methods based on CFA interpolation pattern, and identification methods based on statistical features of images.

(1) Image source identification based on SPN.

Due to the limitation of manufacturing technique and material properties, it is inevitably that imaging devices have some internal defects. In the process of image generation, these defects will present in image in the form of special pixels or pattern noise. Therefore, if such special pixels and pattern noise can be extracted

☆This work was supported by the National Natural Science Foundation of China under Grant no. 61075007, The Natural Science Foundation of Shaanxi Province of China under Grant no. 2015JM6262, The foundation of the State Key Laboratory of Aerospace Dynamics.

* Corresponding author.
E-mail address: xfwang66@sina.com.cn (X. Wang).

http://dx.doi.org/10.1016/j.neucom.2016.05.012
0925-2312/

and matched with the reference pattern of certain camera, then image source can be identified.

To this end, many methods were proposed to detect the correlation between noise residual and camera reference pattern. Lukas et al. [1] proposed such a method. In [1], authors calculated the correlation between noise residual of a specific image and camera reference pattern of investigated camera to decide whether a tested image was captured by this type of camera. Considering that noise residual is usually caused by CFA interpolation, scene content and other noise, Chen et al. proposed an algorithm [2] that considered the identification task as a joint estimation and detection problem, and they used a Maximum Likelihood estimator of the Photo-response non-uniformity noise (PRNU) in a specific image. Work [3] reported that different image regions have different SPN information. So they selected best regions according to local information, and only the PRNU of selected regions were used to calculate the correlation between PRNU of the image and PRNU of testing camera. Work [4] proposed a method based on cross-correlation between reference PRNU and image residual noise, and located the position of the sharp peak correlation value. Finally, the position information was considered as distinguishable feature of the image.

However, in frequency domain, the SPN is usually contaminated by image content, non- unique artifacts of JPEG compression, and other factors. Thus, for source camera identification methods that are based on SPN, the identification performance heavily depends upon the purity of estimated SPN. To eliminate contamination and extract an accurate SPN, there were many works to focus on enhancing SPN. Work [5] suggested that an enhanced SPN could be obtained by assigning weighting factors inversely proportional to the magnitude of the SPN components. Kang et al. [6] putted forward a method that is based on the SPN of camera reference phase. Comparing with Goljan et al. test statistic peak to correlation energy (PCE) [7], work [6] can lower the false positive rate to be a half of the former. In [8], authors assumed that the SPN is a white signal. They extracted SPN directly from the spatial domain with a pixel-wise adaptive Wiener filter. Experimental results showed that the method achieved satisfactory receiver operating characteristic (ROC) performance among all of the state-of-the-art camera source identification schemes, and could resist JPEG compression (e.g. with a quality factor of 90%) simultaneously. Recently, Tomioka et al. [9] presented a novel source camera identification method using the pair-wise magnitude relations of image sensor noise. Since the probability that the pair-wise magnitude relation of different cluster-pairs is identical for images taken by the same camera is higher than that of images taken by different cameras, the camera source can be identified.

This kind of methods can identify the source cameras of query images. However, strictly speaking, these methods are not really passive forensics. The reason is that the reference pattern of the tested camera must be known in advance. While, in order to obtain the reference pattern of tested camera, it is necessary to obtain a large amount of images that are taken by the tested camera, and these images must include flat-field regions.

(2) Image source identification based on CFA.

The main idea of this type of methods dependents on following facts: most cameras have a CCD (Charged Coupled Device) sensor, to render color, the light should be filtered by CFA before reaching the sensor. The CFA pattern arrangement depends on the manufacturer. As a result, the sensor output is a mosaic of e.g. red, green and blue pixels arranged on a single layer. To obtain canonical 3-channels representation, the signal needs to be interpolated. The interpolation model leads to a periodic characteristic among image pixels. However, interpolation models used by different manufacturers are not the same, so CFA interpolation models can be used as the clue of source camera identification. According to this ideal, there are two types of methods in existing literatures, one is based on inter-pixel correlation pattern, and other is based on inter-channel correlation pattern.

The earlier work was proposed by Bayram et al. [10]. In their method, the Expectation- Maximization (EM) algorithm was used to estimate the weighting (interpolation) coefficients which designate the amount of contribution from each pixel in the CFA interpolation kernel. Then the set of weighting coefficients obtained from an image, and the peak location and magnitudes in frequency spectrum were used to design classifier to distinguish source camera. The result was not satisfactory for the heavily compressed images. In order to overcome this defect, authors improved their method in [11], where the periodicity in the second-order derivatives on smooth and non-smooth parts of images was captured separately. Long et al. [12] presented a quadratic pixel correlation model, in which, a coefficient matrix was obtained for each color channel, and the principal components were extracted and fed to a feed-forward BP neural network for source camera identification. Swaminathan et al. [13] presented a method that identified the CFA pattern and estimated the interpolation parameters based on minimum mean-square estimate. Instead of using traditional correlation between pixels, Ho et al. [14] used the correlation between inter-channel, and developed a method through the variance of color difference planes. Resent work [15] presented an improved algorithm of [14], in which, two variance maps were extracted by estimating the variances of each component of green-to-red and green-to-blue spectrum differences, respectively, and then the shape and texture features were obtained for camera model identification.

Though this kind of methods is very popular, there are two inherent restrictions. Firstly, various CFA models must be tried for coefficient estimation during the detection process in that the CFA pattern of an image is often unknown. This incurs high computational complexity. Secondly, both inter-pixel and inter-channel correlation pattern are sensitive to JPEG compression, since compression can be regarded as a local homogenization and attenuates the characteristics of local correlation pattern. Therefore, this kind of methods often have not satisfactory detection accuracy for images that undergone JPEG compression.

(3) Image source identification based on image statistical features.

Since different brands and different models digital cameras are differences in CFA interpolation algorithm and parameter design, thus images taken by different camera have different statistical characteristics. According to this theory, image statistical characteristics can be used to distinguish tested camera.

The earlier method was proposed by Kharrazi et al. [16]. In their work, 34-dimensional features were consisted of average pixel value, RGB pair correlation, neighbor distribution center of mass, RGB pair energy ratio, wavelet domain statistics, Image Quality Metrics (IQM), and so on. These features were fed to a SVM classifier to identify camera source. Wang et al. [17] proposed an effective approach, in which, 216-dimensional higher-order wavelet features and 135-dimensional wavelet coefficient co-occurrence features were extracted from tested images, and a Sequential Forward Feature Selection (SFFS) method was applied to reduce redundancy and correlation, finally, a multi-class SVM was used to identify source cameras. The accuracy of this approach is experimentally proved on images of six cameras as high as 98%. Hu et al. [18] and Chen et al. [19] combined the features proposed in [16] and [22] to form 102-dimensional feature vectors. These features were fed to a SVM classifier for identifying source cameras. Wahab et al. [20] developed a new approach based on the conditional probabilities (CP) features. In their work, the CP of selected block-wise Discrete Cosine Transform (DCT) coefficients was exploited. The average identification accuracy of this approach