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A local variance based approach to alleviate the scene content interference for source camera identification

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ABSTRACT

Identifying the source camera of images is becoming increasingly important nowadays. A popular approach is to use a type of pattern noise called photo-response non-uniformity (PRNU). The noise of image contains the patterns which can be used as a fingerprint. Despite that, the PRNU-based approach is sensitive towards scene content and image intensity. The identification is poor in areas having low or saturated intensity, or in areas with complicated texture. The reliability of different regions is difficult to model in that it depends on the interaction of scene content and the characteristics of the denoising filter used to extract the noise. In this paper, we showed that the local variance of the noise residual can measure the reliability of the pixel for PRNU-based source camera identification. Hence, we proposed to use local variance to characterize the severeness of the scene content artifacts. The local variance is then incorporated to the general matched filter and peak to correlation energy (PCE) detector to provide an optimal framework for signal detection. The proposed method is tested against several state-of-art methods. The experimental results show that the local variance based approach outperformed other state-of-the-art methods in terms of identification accuracy.

Introduction

Due to the popularity of image capturing devices, digital images could be frequently presented as evidence in the court. Reliable identification of digital image origins will be very useful for law enforcement. For example, in the cases involving illegal images, identification of the possessor of the source camera taking these illegal images would be important in the investigation. Clues from different stages of the image acquisition process can be used to identify the source camera of the query image. The simplest approach is to examine the electronic file itself and look for clues in headers or other associated information. One example is the Exchangeable Image File (EXIF) header that contains information about the digital camera type and the conditions under which the image was taken. However, these data may not be available if the image is resaved in a different format or recompressed. Besides, the header information can be easily modified which undermines the credibility of this method. Another approach of source identification is to embed digital watermark in the image that contains information about the digital camera (Blythe and Fridrich, 2004, 11–13) (Wong, 1998, 374–379). However, adding watermarking feature in cameras incurs additional cost. Most cameras also do not support this feature (Sencar and Memon, 2008, 325–348).

A feature based approach which utilizes the artifacts produced by image processing operations for source identification was considered in (Mehdi et al., 2004, 709–712 Vol. 1). Features were extracted from digital images which were then used to train the support vector machine (SVM) for source identification. However, the identification accuracy was limited. Pixel defects can also be employed to identify the camera source. This method, however, has limitation because defective pixels may not exist or may be eliminated by post processing. Recently, a powerful approach based on the photo-response non-uniformity (PRNU) has been proposed (Lukas et al. 2006, 205–214). The PRNU provides unique characteristics of a specific digital camera. It arises from the imperfection during the manufacturing of the silicon wafer in the imaging sensor. The imperfection makes each pixel respond differently to the illumination of light (Li and Li, 2010, 3052–3055). Artifacts resulting from the pixel by pixel difference will then exist in all images taken by that particular camera. This unique artifact called PRNU can be used as the fingerprint of a specific camera. Since the PRNU is different from one camera to another, it can identify not only camera models but also individual cameras of the same model.

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Moreover, the PRNU signal remains more or less unchanged after operations like lossy compression, cropping, printing, downsizing etc (Fridrich, 2009, 26–37). (Rosenfeld and Sencar, 2009, 72540M-72540M-7) (Goljan et al., 2008, 68190I–68190I-12) (Alles et al., 2008, 557–567).

To obtain the PRNU signal, denoising is applied to those images under test and the resultant noise residual forms the PRNU signal. One problem of using PRNU for source camera identification is that the scene content can severely contaminate the extracted PRNU. If images contain a lot of textures, have low or saturated intensities, the accuracy of identification will drop. Several methods have been proposed to suppress the influence of scene content. In (Chen et al, 2007a, 65050P–65050P-13), a maximum likelihood method is proposed to estimate the camera reference PRNU. Kang et al. (Kang et al., 2012, 393–402) proposed to whiten the PRNU in the frequency domain to estimate the reference PRNU. The approaches which make use of the idea of reliable regions have been proposed in (Li, 2010, 280–287) (McCloskey, 2008, 1–6) (Chan et al., 2013, 215–225) (Shi et al., 2014, 1–7). In (Chan et al., 2013, 215–225), (Shi et al., 2014, 1–7), learning based methods are adopted, in which a training phase is required before camera identification. In (Li, 2010, 280–287), Li made a hypothesis that the stronger a signal component is, the more likely that it is associated with strong scene details, and thus the less trustworthy the component should be. Based on this hypothesis, Li proposed five different models to shrink the noise residuals with high magnitude. However, there is no proof showing that the five models give the optimal weightings.

Although methods that reduced the scene content influence has been proposed, it is very important to allocate appropriate weightings to different regions of the image. If the weightings are assigned too aggressively, for example assigning a weighting of 1 to the smoothest regions and 0 to other regions, the decision statistics obtained will be highly unstable because only small portion out of the whole image is utilized for the detection. On the contrary, if the weightings are assigned too conservatively, the improvement of accuracy will not be significant. This problem is illustrated in Fig. 1. Fig. 1 shows the distribution of the decision statistics for positive and negative images. Fig. 1 (a) is the distributions when no weighting is applied and (b) is the distributions when an over aggressive weighting is adopted. In the case of (b), although the mean correlation for matching case becomes larger, the chance of false detection is higher because the standard deviation of correlation becomes larger which results in a larger overlapping between the positive and negative situations. This example illustrates the intuitive idea that assigning larger weights to the reliable regions may fail to improve the detection accuracy. Hence, determining the optimal weights that give the highest detection accuracy is not a straight forward task.

In this paper, on one hand, we study how the noise residual strength affects the source camera detection accuracy. On the other hand, we proposed a method to obtain the weighting for each pixel based on the general matched filter which has been proved to be the optimal detector. The rest of the paper is organized as follows. In section Camera identification with PRNU, the use of PRNU for source camera identification is reviewed. Then the motivation and details of the proposed algorithm is presented in section The proposed method. Experimental results and analysis are given in section Experimental result. Finally, section Conclusion concludes this paper.

Camera identification with PRNU

The general PRNU-based camera identification approach includes two phases: camera fingerprint construction and testing. In the first phase, the PRNU signal for each source camera was constructed. In the testing phase, the noise residue signal from the testing image was extracted as in the first phase. Correlation between the noise residue from the testing image and the camera PRNU was then calculated to decide whether the testing image was taken from that particular camera.

PRNU extraction from images

The PRNU-based approach was proposed by Lukas and Fridrich in (Lukas et al. 2006, 205–214). To decide whether an image was taken by the reference camera or not, a set of images from the reference camera was obtained. These images were then denoised using a denoising filter to generate a set of noise residues. The PRNU of a camera C (called the reference PRNU), denoted as $\widehat{\mathbf{K}}_C$, was obtained by taking the average of these noise residues, i.e.,

$$\widehat{\mathbf{K}}_C = 1/N\sum_{k=1}^{N}\mathbf{W}_k, \quad (1)$$

where $\mathbf{W}_k$ is the noise residue from the kth image and N is the number of images used to estimate the PRNU. Instead of using a

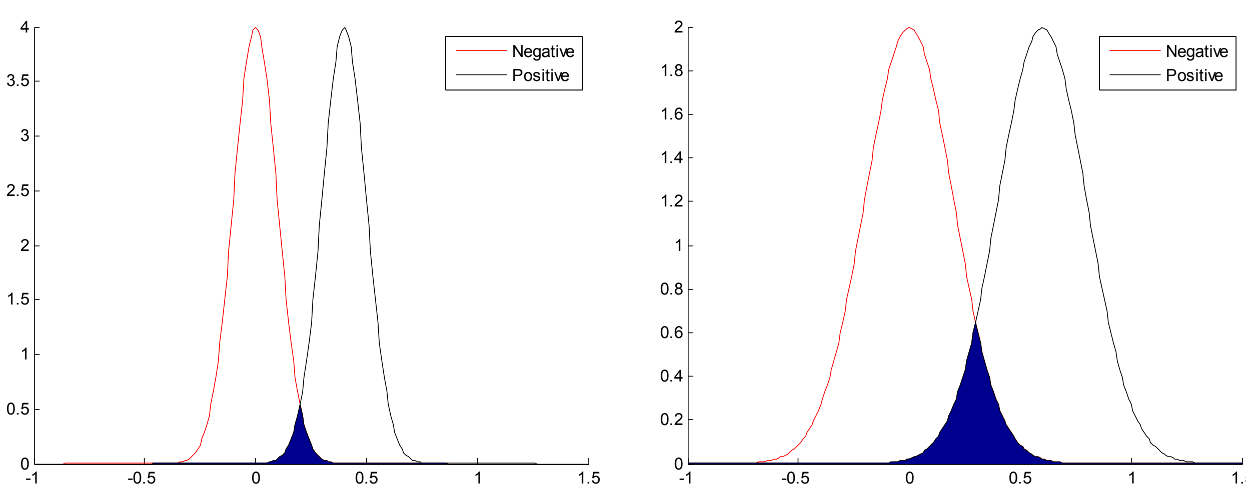

Fig. 1. Illustration of aggressive weighting allocation problem. The left figure shows the distribution of the positive and negative samples when no weighting is applied. The right figure shows distribution when the over aggressive weightings are applied to the test.

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