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Eliminating the effects of illumination condition in feature based camera model identification☆

Udaya Sameer Venkata*, Ruchira Naskar

Department of Computer Science and Engineering, National Institute of Technology, Rourkela, Rourkela 769008, India

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ABSTRACT

State-of-the-art techniques for Camera Model Identification operate by extracting different features from the training image set and incorporating those features to predict the source of test images using machine learning. Though the existing approaches perform efficiently for images captured in natural daylight or bright illumination conditions, the state-of-the-art lacks sufficient experiments and results to evaluate efficiency of such schemes for images captured in dark illumination conditions. In this paper, we present a set of experiments to assess the impact of illumination conditions, on image source classification problem, and also propose an image filtering based technique to eliminate the adverse effects of scene illumination on source classification accuracy. Our experimental results prove that the performance efficiency of existing feature based source classification techniques, is indeed dependent on the illumination conditions. The proposed strategy enables our source classification model to achieve high efficiency as compared to the state-of-the-art, under all illumination conditions.

1. Introduction

Source Camera Identification (SCI) is a problem in Digital Forensics which can be stated as the task of correctly identifying the source camera of an image under question, from out of a closed set of accessible cameras. The application of this problem is majorly to establish evidences in the court of law towards investigation of crimes, such as child pornography, settling copy-right issues by finding the authentic owner of an image, and many other such scenarios relevant in today's digital age.

In this paper, we investigate the *effect of illumination conditions* in machine learning based camera model identification and demonstrate (through a set of experiments) that the source classification accuracy of such methods, is largely dependent on illumination conditions. Subsequently, in this paper we also build a machine learning model for camera model identification that is not susceptible to the illumination conditions of a scene. Summarily, our contribution in this paper is two-folds: (A) to investigate and hence prove the existence and the effect of illumination conditions have in features based camera model identification, and (B) to develop a machine learning model by eliminating the effect of illumination conditions for blind source classification.

There are broadly three approaches to solve the camera model identification problem. They are image meta data based approaches, sensor fingerprint based approaches and image features based approaches which use machine learning techniques. The image meta data [1] based source identification schemes rely on the meta data or information about an image which is added by the camera at the time of image post-processing. However, such schemes suffer heavily due to the present day incredibility of digital image meta data, caused by the influx of easy-to-use image editing softwares that can alter/modify the meta data information without minimal hint to the viewers. The sensor fingerprint based source identification techniques inspired by [2], use the noise residual in an image as a unique fingerprint trait to attribute an image to its sensor. These works depend on the fact that the sensor pattern noise in a sensor is unique for a camera model. Finding the noise residual in a test image and correlation with the sensor pattern noises of the cameras at hand to find out the possible source device which captured the given image.

The machine learning based source classification techniques [3–9] which operate by extracting suitable features from sample image sets of candidate cameras, and hence, train a machine learning model to accurately predict the source of an image under question. Different researchers have used different sets of image features in such machine learning based models [3,4,7]. However, the *effect of illumination conditions* in camera model identification has not been investigated sufficiently in the current literature for feature based camera model

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* Corresponding author.
E-mail addresses: 515cs1003@nitrkl.ac.in (U.S. Venkata), naskarr@nitrkl.ac.in (R. Naskar).

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identification techniques. In this paper, we establish this problem with respect to the change in behaviour/performance of source classification methods, as the training/testing datasets are varied from natural images to dark images.

Our experimental results prove that the proposed scene dependency removal technique minimizes the impact of illumination conditions on camera model identification, and achieve considerably high classification accuracy as compared to the state-of-the-art. This accuracy remains consistent even during the classification of source devices, belonging to the same make but different models (*intra-make device classification*). We have tested the performance of the proposed method on the standard benchmark forensic database of Dresden images [6]. In this paper, we also perform an *overfitting test* on the proposed model to ensure that it is free from overfitting errors.

The rest of the paper is organized as follows. In Section 3, we show a set of experiments to demonstrate the existence of scene dependency in machine learning based source identification. In Section 4, we present our proposed scheme to eliminate the problem of scene dependency in source classification. In Section 5, we provide our experimental results pertaining to the proposed scheme. Finally, we conclude the paper in Section 6.

2. Background

2.1. Related works

The problem of camera model identification came to the fore majorly with the works of Kharrazi et al. [3] and Lukas et al. [2]. The former work deals with the problem of camera model identification by extracting various image features and using machine learning techniques to classify the given images into their source classes. The latter work started exploring camera fingerprinting techniques, where a unique trait of a camera model (in this case *Photo Response Non Uniformity* (PRNU) noise), is used to attribute an image to its source camera. Since then, a number of researchers around the world followed similar approaches, based on either machine learning or camera fingerprinting principles, for image source identification.

In this section, we first discuss about the machine learning based techniques, followed by camera fingerprinting techniques. Kharrazi et al. [3] used Image Quality Metrics (IQM) as the features for source classification. The authors believed that the color processing or transformation of a digital image is majorly dependent on the camera model and different camera models would have different Color Filter Array (CFA) configurations and demosaicing algorithms. Thus, the IQM features which are traditionally adopted in *Steganographic algorithms* [10], found use in source identification problem also. After the work of Sayood et al. [11] the statistical significance of such IQM features became widely known. Similarly, with the work of Lyu et al. [12] the use of High Order Wavelet Statistics (HOWS) as image features in source classification problem, was established. Another significant research towards machine learning based camera model identification was by Celiktutan et al. [4], where the authors have used features like Binary Similarity Measures (BSM), IQM and HOWS, and machine learning techniques such as *feature selection* and *decision fusion* in source classification. Tsai et al. [5] and Hu et al. [13] investigated feature selection procedures and issues in selecting features, respectively. More recent works following machine learning based approaches for image source identification are [14,15]. In [14], the authors used HOWS features, extracted from the PRNU noise residuals of an image, and in [15] the authors proposed a new set of Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) based features for camera model identification.

On the other hand, the camera fingerprint based techniques also were explored extensively. PRNU is a component of sensor pattern noise, that gets accumulated in an image due to sensor imperfections. PRNU was identified as a camera fingerprint, and was used by Lukas et al. [2] for source identification problem. After Lukas et al. proposed the use of PRNU and a hypothesis testing strategy to identify image sources, several researchers have enhanced this approach further. For example, Li et al. [16], suggested an enhancement to extracting sensor pattern noise by attenuating the magnitude of other details than sensor noise by following a weighting strategy of assigning lesser weights to strong components in the wavelet transform of the image. Other researches in this direction include the works of Chen et al. [17] and Goljan et al. [18]. Such camera fingerprint matching works utilize correlation between camera models and test images, by forming a similarity matrix of PRNU components, and then employ statistical techniques like Hypothesis testing to map an image to its source. Kang et al. [19] proposed a Phase Sensor Pattern Noise mechanism to handle the impact of image content and JPEG compression artefacts. The authors also proposed Circular Correlation Norm (CCN) as test statistics, instead of widely followed peak to correlation energy (PCE) measure, and achieved a lower false positive rate than the later. A recent work by Bayram et al. [20] addressed the one-to-many matching of fingerprints in a large database, by providing a group-testing strategy. Zeng et al. [21] proposed a framework for Camera Model Identification as a *Bayesian Game*, following the properties of Game Theory. The authors studied the interplay between the sensor-based camera source identification, and the *fingerprint-copy attack* [22]. They also proposed a counter measure to overcome fingerprint-copy attack. The noise level based counter measure proposed here by the authors, performs computationally faster than the triangle test proposed in [23]. However, due to the recent advancements in *counter-forensics* [24,25], the PRNU based methods of source identification have become highly vulnerable, especially to *source anonymization* attacks on digital images.

Until the development of Dresden image database [6] by Gloe et al., there was no benchmark dataset for standardizing forensic researches. Gloe et al. [7] experimented thoroughly with camera source identification using feature selection strategies on Dresden image dataset. In [6], for the first time Gloe et al. addressed the *open set problem*, which is to detect the source of an image out of a set of possible cameras, one or more of which may not be physically accessible to the forensic analyser. Tsai et al. [8] also addressed camera source identification problem on Dresden image dataset using a variety of feature selection strategies, used decision fusion techniques and also experimented with various image sets of different sizes. In recent times, Huang et al. [9] addressed a very important problem in practical context, viz., to detect the existence of unknown camera models which is also known as open set challenge as discussed earlier. They addressed this problem through a strategic use of (K + 1)-classification. Other state-of-the-art techniques for camera model identification are based on principles such as exploitation of CFA interpolation [26], traces of sensor dust [27], DCT coefficient statistics [28] and image source clustering [29]. In this paper, we focus on feature extraction based source classification.

In feature based camera source identification techniques the effect of illumination conditions is not addressed before. The features used in literature like IQM, HOWS, PRNU based, etc. extract information mostly from the natural day light images, thus the feature based techniques need a study on whether the illumination conditions play a role on the classification. In this paper we addressed this question experimentally and proposed an approach through the usage of JPEG compression, SPIHT compression and thus improving the classification accuracy.

2.2. Image formation pipeline in digital cameras

During image formation in a digital camera, the light rays reflected by a natural scene object passes through the camera lens and falls on its sensor, hence forming the raw sensor image. The raw image undergoes a number of transformations (post-processing steps) to produce the final digital image. Fig. 1 shows the image processing pipeline in modern-day digital cameras. After different in-camera corrections like noise