TECHNIQUES FOR SOURCE CAMERA IDENTIFICATION

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Abstract

Digital image forensics has lately become one of the very important applications to identify the characteristics and the originality of the digital devices. This paper studies the recent developments in the field of image source identification. Proposed techniques in the literature are categorized into five primary areas based on source model identification: Metadata, Image Features, CFA and Demosaicing Artifacts, Lens Distortions and Wavelet Transforms. The main idea of the proposed approaches in each category is described in detail, and reported results are discussed to evaluate the potential of the methods.

Keywords - Image forensics, source camera identification, classification, SVM.

1 INTRODUCTION

Image source identification research investigates the design of techniques to identify the characteristics of digital data acquisition device (e.g., digital camera and cell-phone) used in the generation of an image. These techniques are expected to achieve two major outcomes. The first is the class (model) properties of the source, and the second is the individual source properties.

The success of image source identification techniques depends on the assumption that all images acquired by an image acquisition device will exhibit certain characteristics that are intrinsic to the acquisition devices because of their (proprietary) image formation pipeline and the unique hardware components they deploy, regardless of the content of the image. (It should be noted that such devices generally encode the device related information, like model, type, date and time, and compression details, in the image header, e.g., EXIF header. However, since this information can be easily modified or removed, it cannot be used for forensics purposes).

1.1 Image Formation in Digital Cameras

The design of image source identification techniques requires an understanding of the physics and operation of these devices. The general structure and sequence of stages of image formation pipeline remains similar for almost all digital cameras, although much of the details are kept as proprietary information of each manufacturer.

Consumer level digital cameras consist of a lens system, sampling filters, colour filter array, imaging sensor and a digital image processor [1]. The lens system is essentially composed of a lens and the mechanisms to control exposure, focusing, and image stabilization to collect and control the light from the scene. After the light enters the camera through the lens, it goes through a combination of filters that includes at least the infra-red and anti-aliasing filters to ensure maximum visible quality. The light is then focused onto imaging sensor, an array of rows of columns of light-sensing elements called pixels. Digital cameras deploy charge-coupled device (CCD) or complimentary metal-oxide semiconductor (CMOS) type of imaging sensors. Each light sensing element of sensor array integrates the incident light over the whole spectrum and obtains an electric signal representation of the scenery. Since each imaging sensor element is essentially monochromatic, capturing colour images requires separate sensors for each colour component. However, due to cost considerations, in most digital cameras, only a single sensor is used along with a colour filter array (CFA). The CFA arranges pixels in a pattern so that each element has a different spectral filter. Hence, each element only senses one band of wavelength, and the raw image collected from the imaging sensor is a mosaic of different colours and varying intensity values. The CFA patterns are most generally comprised of red-green-blue (RGB) and cyan-magenta-yellow (CMY) colour components. The measured colour values are passed to a digital image processor which performs a number of operations to produce a visually pleasing image. As each sub-partition of pixels only provide information about a number of colour component values, the missing colour values for each pixel need to be obtained through a demosaicing operation. This is followed by other forms of processing like white point correction, image sharpening, aperture correction, gamma correction and compression. Although the operations and stages explained here are standard stages in a digital camera pipeline, the exact processing detail in each stage varies from one manufacturer to the other, and even in different camera models manufactured by the same company.

2 SOURCE MODEL IDENTIFICATION

The features that are used to differentiate camera-models are derived based on the differences in processing techniques and the component technologies.

The deficiency of this methodology, in general, is that many models and brands use components by a few manufacturers, and processing steps/algorithms remain the same or very similar among different models of a brand. Hence, reliable identification of a source camera-model depends on characterization of various model dependent features as explained below.

2.1 Techniques Based on Metadata

These are the simplest although they strongly depend on the data the maker inserts as metadata when the picture is taken. Furthermore, this method is the most vulnerable to malicious changes by third parties. Nevertheless, once it is proven that there is no kind of external modification, analysing the large amount of metadata can greatly help the forensic analyst.

There are a huge amount of papers referencing the different types of metadata in pictures for search and classification purposes [2, 3, 4, 5]. As stated before, these kinds of techniques, though simplest, depend on the metadata the maker may introduce. In fact, the most followed specification to identify the source of the camera, Exif [6], has two specific tags: “Make”' and “Model”, unfortunately filling data in those tags is not mandatory.

2.2 Techniques Based on Image Features

Tsai et al in [7] proposed approach methods to determine source camera or mobile phone with camera. They used a set of image features to find out about the characteristics of the camera. The features include colour features, quality Features and Image Characteristics of frequency domain. They adopt the Wavelet Transform method for calculating wavelet domain statistics and add the SVM optimal parameter setting to search step to enhance the identification rate of their previous research. The results obtained over four cameras models from two different camera brands yielded average accuracies close to 92%.

McKay et al in [8] extends *Image Source Identification* to device types such as cell phones cameras, digital cameras, scanners and computer-graphics. To achieve this, firstly they should find sources of variation among different types of devices and between different models of a device. This can be done using the dissimilarities in the image acquisition process of the imaging devices to develop two groups of features, namely colour interpolation coefficients and the noise features. They can also use these features to obtain a correct identification. Their experiments used five different models of cell phone, five models of digital cameras and four scanner models to identify the source type. The overall results were an identification accuracy of 93.75%. In their analysis of the identifying device brand/model of cell phone, obtained accuracy close to 97.7% for five models.

Jiang et al in [9] point out the fact that different patterns of sensor noise have been used for source identification successfully. However, these techniques present a particular problem since most of the time once the photos have been obtained are reprocessed, e.g., rescaling, cropping, compressing, etc. The image modifications generally destroy the fingerprint that the sensor noise could leave invalidating the sensor noise based approaches.

As a result of the previously mentioned issue, the authors propose a method that employs the marginal density DCT (Discrete Cosine Transform) coefficients in low-frequency coordinates and neighbouring joint density features on both intra-block and inter-block from the DCT domain. Additionally, they use hierarchical clustering and SVM with linear and RBF kernel to distinguish the smartphone source and processing operations applied. They experimented with different scale factors images belonging to five different smartphone models from four manufactures, obtaining a mean testing accuracy between 86.36% and 99.91%, and achieving better results while using linear kernel. Despite these satisfactory results, they could be enhanced by optimizing the kernel parameters, increasing de image data set and adopting a sophisticated feature selection algorithm.

2.3 Techniques Based on CFA and Demosaicing Artifacts

The choice of CFA and the specifics of the demosaicking algorithm are some of the most pronounced differences among different digital camera-models. In digital cameras with single imaging sensors, the use of demosaicking algorithms is crucial for correct rendering of high spatial frequency image details, and it uniquely impacts the edge and colour quality of an image. Essentially, demosaicking is a form of interpolation which in effect introduces a specific type of inter-dependency (correlations) between colour values of image pixels. The specific form of these dependencies can be extracted from the images to fingerprint different demosaicking algorithms and to determine the source camera-model of an image. Brayman et al in [1], describe their approaches to identify, detect and classify traces of demosaicking operation. They rely on two methods: The first method is based on the use of Expectation-Maximization algorithm which analyses the correlation of each pixel value to its neighbours; the second method is based on analysing inter-pixel differences. They divide their experiments into two categories. The first category of experiments was performed to assess the accuracy of camera-model identification method and the second category of experiments evaluated the improvement in the accuracy of individual camera identification method.

The accuracy in identifying the source of an image among four and five camera-models is measured as 88% and 84.8%, respectively, using images captured under automatic settings and at highest compression quality levels.

In [10], Çeliktutan et al use a set of Binary similarity measures, which are the metrics used for measuring the similarity between the bit-planes of an image. The underlying assumption is that proprietary CFA interpolation algorithm leaves correlations across adjacent bit-planes of an image that can be represented by these measures. 108 binary similarity measures are obtained for image classification purpose. The results of your experiment for a group of 9 cameras has accuracy is only 62% collecting 200 images from each one of the maximum resolution, size of 640x480 pixels, at day light and auto-focus mode.

2.4 Techniques Based on the Use of Sensor Imperfection

They can be divided into two large branches: pixel defects or sensor noise patterns.

Geradts et al [11] examine CCD pixel defects but it is not fully relevant in our case (CMOS). This technique includes point defects, hot points, dead pixel, pixel traps and cluster defects. The result noted that each one of the cameras had a different defect pattern. Nevertheless, it also noted that the number of defects in the pixels for a camera differed between pictures and varies greatly depending on the content of the image. It was also revealed that the number of defects varied at different temperatures. Finally, the study found that cameras with high-end CCD did not have this kind of problem, meaning that not all cameras suffered from this issue. It is also true that most cameras have additional mechanisms to compensate for this kind of problem.

In [12] Luka et al propose a method based on the non-uniformity of the pixels (PNU Pixel Non-Uniformity), which is a great source for the retrieval of noise patterns, which allows identifying the sensors and therefore the camera. The result for pictures with different sizes and cropped images is not satisfactory [13].

Costa et al [14] Postulate an approach for source camera attribution considering an Open Set scenario, which means that it cannot be taken for granted a full access to all possible source cameras. This proposal comprises three strands: definition of regions of interest, feature characterization, and source camera attribution. Different regions of the images can contain different information about the fingerprint of the source camera. This approach in contrast to others considers different areas of interest and not just the central region of the image. For each image, nine regions of interest (ROI) are defined as illustrated in Fig 1.

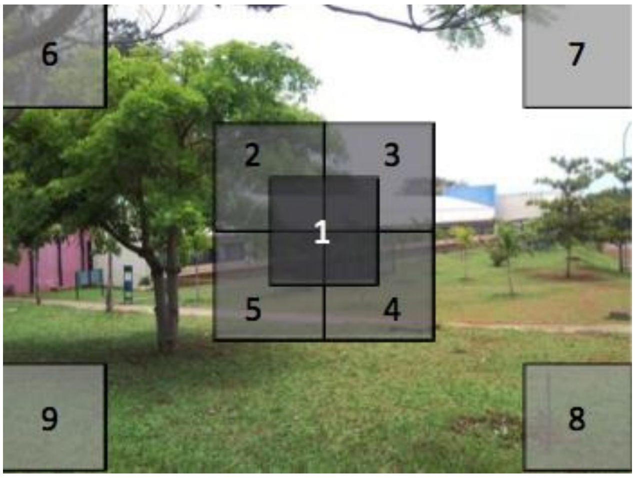

Fig. 1. Regions of interest [14]

It is assumed that these regions coincide with the principal axis of the lens and should have more scene details because amateur photographers usually focus the object of interest in the centre of the lens. Moreover regions 6 to 9 provide important information because some cameras have an effect generated by the vignetting, meaning a radial intensity downfall from the centre of the image which causes a loss of brightness or saturation at the periphery.

An important aspect to note from this kind of region characterization is that it allows comparing images with different resolutions without colour interpolation artefacts, and it is not necessary to do zero-padding, for instance, when comparing images of different sizes.

For the purpose of obtaining a feature characterization, they compute the sensor pattern noise considering the R, G, and B channels separately. In addition, they calculated the SPN for the Y channel (luminance, from YCbCr colour space) which is a combination of R, G and B channels (as a gray scale version of the image). A feature vector is formed considering the correlation between each ROI yielding in a total of 36 features to represent each image; afterwards images taken by the camera under investigation are labelled as the positive class and the remaining available cameras as the negative classes.

Finally, they came forward with a proposal to solve the source attribution problem in an open set scenario. A SVM with a RBF kernel is used to find a classifier from the training set of examples considering the positive and the available negative samples.

They take into consideration the unknown classes by moving the decision hyper plane by a value inwards to the positive class or outwards in the direction of the negative known class(es), in this way they can vary how strict they want to be in order to determine if an image belongs to a class or not. They loosely call this process as Decision Boundary Carving (DBC).

In their experiments they use a dataset with 25 digital cameras from 9 manufacturers, 150 images in JPEG format were generated for each camera with different configurations of light, zoom and flash. They achieved 94.49%, 96.77%, and 98.10% of accuracy using open sets with 2/25, 5/25, and 15/25 cameras respectively. Defining an open set with x/y as the set of y cameras where x cameras are used for training and for testing the images can belong to any of the x known cameras as well as to the other y-x unknown cameras.

2.5 Techniques Based on Wavelet Transforms

In Meng et al [15] proposes a feature-based method for source camera identification. This method employs the magnitude and phase statistics of bi-coherence along with wavelet coefficient statistics, focusing on capturing the unique non-linear distortions on higher-order image statistics produced by different cameras and the impact of image processing operations on the wavelet domain.

First, in order to obtain the non-linear distortions characterization Bi-Coherence Features are extracted: The normalized bi-spectrum of the signal is estimated by dividing the signal into N (possibly overlapping) segments, computing the Fourier transform of each segment, and averaging the individual estimates. The mean of the magnitude and the negative phase entropy of the bi-coherence are computed as statistic features.

For reducing memory and the computational overhead implicated when calculating the total four-dimensional bi-coherence of the images, they decided to restrict their analysis to one-dimensional row, column and radial slices through the centre of the images. It is interesting to note that no rigorous constraints are placed on image sample selection since when applying bi-coherence statistics it is not necessary to extract information associated with image content (e. g., line segments).

Next, Four-scale wavelet decomposition is employed to split the frequency space into four scales and orientations. Then, four statistics (mean, variance, skewness and kurtosis) of the subband coefficients and the linear prediction errors at each orientation, scale and colour channel are computed. These statistics compose the second group of statistical feature vectors used for source camera identification. Once the bi-coherence and wavelet statistics are computed, the sequential forward featured selection (SFFS) algorithm [16] is used to reduce the correlation among features and computing load, while keeping the same classification accuracy. The SFFS method analyses all the features and builds the most significant set from them by adding and removing features until no more improvements are available.

Finally, the most representative features are classified by multi-class SVM using a C-support vector classification with non-linear RBF kernel with two tuneable parameters.

They performed experiments under the following conditions: six different model cameras from four manufactures, image of different resolutions, JPEG format, and a total of 2,100 images obtained from typical shots varying from nature scenes to close-ups of people (350 images from each camera).

As a result, they obtained a noteworthy average identification accuracy that exceeds the 97% distinguishing different models of the same brand. However, further improvements could be made by incorporating features from other techniques such as the following approach.

Wang et al [17] Describe an approach to source camera identification extracting and classifying wavelet statistic features, this method is mainly composed of three phases: Wavelet Features Extraction, Wavelet Features Selection, and Wavelet Feature Classification.

Outstanding features of wavelets domain are extracted integrating the statistical model for natural digital image from the wavelet coefficients including 216 higher-order wavelet features and 135 wavelet coefficient co-occurrence statistics. Being considered as the most significant in the identification process, features from the wavelet domain are preferred over spatial features (image color and Image Quality Metrics IQM) and Colour Filter Array (CFA). Analogously to the foregoing method, Four-scale wavelet decomposition is employed based on Separable Quadrate Mirror Filters (QMFs) to split the frequency space, the same four statistics (mean, variance, skewness and kurtosis) and the linear prediction errors are extracted.

The statistics above do not concern the texture correlation, as it has been observed that the co-occurrence features are the best among those used in the image texture feature extraction [18]. Hence, in order to take into account the texture correlation between the wavelet coefficients a co-occurrence matrix is constructed from those coefficients to form an image texture representation and distance calculation is applied in the same orientation to coefficients of co-occurrence matrix between different scales. Then statistical features (energy, entropy, contrast, homogeneity and correlation) are calculated from those distances. The wavelet feature selection and classification processes are performed in the same manner as the above method, using SFFS algorithm to select the most representative features and a multi-class SVM with the non-linear RBF kernel as a classifier.

Under the same conditions as in their prior experiments they succeeded in distinguishing different models of the same camera brand and besides, they increased their past accuracy average to a 98%. This improvement might be due to the consideration of texture features, minimizing the negative effects found in the classifier training when using multiple resolutions in images of the same model and brand. Despite of this result, improvements could still be made by evaluating the robustness of the identification system proposed for the feature vector, and also by extending the image data set in favour of covering more brands, models, textures and contents.

Ozparlak and Avcibas in [19] Exposes a differentiating images technique using transforms from the wavelet family. They propose statistical models for ridgelet, and contourlet subbands.

1. **Ridgelet Transform**: Wavelets perform well at catching zero-dimensional or point singularities. Nevertheless, two-dimensional signals (i.e., images) normally contain one-dimensional singularities (i.e., edges and corners). In order to overcome the above mentioned drawbacks of wavelet, the system called “ridgelets” was developed. The main idea is to use Radon Transform (RAT) to map the line singularities to point singularities. Then, the mapped point singularities in the Radon domain can be effectively handled by the use of wavelet transform.
2. **Contourlet Transform:** In painting lines and contours are used instead of dots to create images. The image wavelet representation is equivalent to using points, in this case the image is not clear and y the image elaboration is harder. Likewise, the representation called "contourlets" [20] is the equivalent to using contour lines, simplifying the image construction and giving it a realistic appearance.

According to the results of previous studies [20], an efficient representation of an image should satisfy the following characteristics:

1. **Multi-resolution**: The representation must be a successful approximation from the image, considering low and high resolutions.
2. **Localization**: the basic elements must be localized in both spatial and frequency domains.
3. **Critical Sampling**: the representation should form a basis or a frame with low level of redundancy.
4. **Directionality**: A remarkable representation must have base elements in different directions.
5. **Anisotropy**: To capture smooth contours in images, the representation should contain basis elements using a variety of elongated shapes with different aspect ratios.

The wavelets transforms cover the first three properties, as ridgelets cover the first four, and contourlets cover all of them. After defining the statistical models for ridgelet and contourlet coefficients, the feature extraction is performed. For each subband of a wavelet-based transform, eight statistical features are calculated from the coefficients themselves and the error prediction between the coefficients by using the statistical models proposed. For the final steps, sequential floating search (SFS) method for the feature selection is applied and a SVM [21] for the feature classification is used.

Since the wavelet-based method considers 216 features (useful only for one dimension representation), while the ridgelet-based approach takes into account 48 features, and contourlets approach considers a total of 768 features. The improved results applying both ridgelet and contourlet transforms are reasonable due to the fact that we get the statistics over more than three directions, taking into account all five of the properties of an efficient image representation. The ridgelet and contourlet models are not only effective at separating the different models, but also they separate the images of the two different cameras or scanners with the same model. However, we could try improvements by experimenting with different feature selection algorithms (e. g. SFFP).

3 CONCLUSIONS

In this paper we have studied different existing techniques for solving the image source identification problem. We categorized them into five primary groups according to the processing strategy that they apply: Metadata, Image Features, CFA and Demosaicking Artefacts, Use of Sensor Imperfection and Wavelet Transforms. The main idea of the proposed approaches in each category is described in detail, and reported results are discussed to evaluate the potential of the methods.

Table 1 summarizes the results obtained in the experiments of the different approaches, pointing out the conditions under which they were performed such as: technique, kind of classifier, classifier kernel type, and number of brands, number of models, and number of images, resolutions, and image formats. Outstanding results were found in the analysis: [14] gets closer to reality while considering an open set scenario where usually it is unknown if the images were generated by one of the cameras under investigation, besides defining the ROIs that allow them to work with different resolutions keeping the important information from images. [18] proposing the use of ridgelet and contourlet transform-based image models, taking into account the properties for efficient image representation.

Several experiments have been focused only on traditional cameras leaving out digital camera mobile phones, this deserves special mention owing to the fact that nowadays the number of this kind of devices is increasing rapidly and this trend is expected to continue. Moreover, some experiments do not contemplate different models from the same brand, and those who do it only show results of experiments with one or two models from one brand. It also should be mentioned that databases of images for training and testing are not large enough to represent realistic scenarios.

Through research significant enhancements have been achieved concerning image source identification. Nonetheless, the next steps in the field should be aimed to bridge the aforementioned remaining gaps.

Table 1. Evaluation of camera identification techniques

Group Technique	Based on Image Features			Based on CFA and Demosaicing Artifacts		Based on Sensor Imperfection			Based on Wavelet Transform		
Technique	[7]	[8]	[9]	[1]	[10]	[11]	[12]	[14]	[15]	[17]	[19]
Classifier	SVM	SVM	SVM	SVM	KNN SVM	NA	NA	SVM	SVM	SVM	SVM
SVM Kernel type	Linear	Linear	Linear and Non-linear RBF	Linear and Non-linear RBF	Linear and Non-linear RBF	NA	NA	Non-linear RBF	Non-linear RBF	Non-linear RBF	Non-linear RBF
Number of brands	2	5	4	5	3	1	5	9	4	4	3
Number of models	4	5	5	2	9	2	9	25	6	6	3
Number of Images per camera	150 (60 training 90 testing)	100 (90 training 10 testing)	599	600	200	NA	320	50	350 (100 training 150 testing)	350 (100 training 150 testing)	2000 (1000 training 1000 testing)
Resolutions	1600x 1200	NA	Different	Different	Different	640x 480	Different	Different	Different	Different	NA
Image Format	JPEG	JPEG	JPEG	JPEG	NA	NA	JPEG	JPEG	JPEG	JPEG	NA
Applied to mobiles	Yes	Yes	Yes	No	Yes	No	No	Only 2 among the 25 cameras	No	No	No
Applied to different models from same brand	Yes	No	Yes	Yes	Yes	NA	Yes	Yes	Yes	Yes	No
Average Accuracy (%)	92	97.7	86.36 - 99.91	88 and 84.8	62	NA	NA	94-98	97	98	Wavelet 93.3 Ridgelet 96.7 Contourlet: 99.7

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