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# Source Camera Identification Forensics Based on Wavelet Features

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***Abstract*—Source camera identification forensics aims at determining and authenticating the original sources of digital images to support forensics and get the trace of digital images. This paper introduces a new wavelet features based passive forensic method for the identification of the image source camera. We consider the intrinsic defects and processing of imaging pipeline within digital cameras can be used to formulate the source camera identification problem. Based on this idea, we extract higher-order wavelet features and wavelet coefficient co-occurrence features from taken images, and then apply Sequential Forward Feature Selection (SFFS) method to reduce the redundancy and correlation of features and finally use multi-class Support Vector Machine (multi-class SVM) as classifier to identify source cameras. The effectiveness of the proposed approach, also in comparison with other approaches, is experimentally proved on images of six digital cameras.**

***Keywords*-digital image forensics; source camera identification; bi-coherence features; wavelet coefficient features; Sequential Forward Feature Selection (SFFS); support vector machine (SVM);**

## I. INTRODUCTION

Digital cameras are today widely in use because of their good performance, convenient usability, and low costs. Digital images taken by them are also widely used not only by the general public for entertainment applications, but also by law enforcement agencies, news media, scientific discovery, and many other applications in various areas, coming with an important issue concerning the integrity of these images. To address such issues, the problem of how to recognize the source camera of a given image has recently received a lot of attention.

Various methods have been proposed to solve the problem of achieving reliable source camera identification. Compared with the active approach of digital watermarking, the passive and blind digital image forensics [1] which are based on recognizing the source camera by only using the taken images provides a more practical, powerful yet challenging approach.

Z. Geradts et al. proposed a method for determining the image origin by detecting the defective sensor points [2]. Lukas et al. proposed another effective identification method that uses the photo-response non-uniformity noise (PRNU), a kind of CCD noise, caused by pixel non-uniformities [3], [4]. While the proposed method is robust under JPEG compression, geometrical operations and noise attacks may prevent correct camera classification [4].

Information about the CFA (Color Filter Array) pattern and the interpolation algorithms used in cameras have also been adopted to identify source camera [5], [6], [7]. However due to the similarities of CFA pattern and interpolation algorithms among different camera brands and especially among different models of the same brand, the methodology based on CFA pattern and color interpolation may not achieve satisfactory accuracy for source camera identification for some camera models.

Kharrazi et al. [8] proposed a feature-based technique in which a classifier is used to determine the source camera according to principles of pattern recognition. Although this method is shown to achieve close to 92% average classification accuracy with sample images covering six different cameras, it fails to identify cameras of the same brand but of different models (The exact experiment results can be found in Section 4). An extension to this feature-based method is by Kai San Choi et al. who make use of the lens radial distortion coefficients of digital cameras as a kind of additional feature [9]. While combining bi-coherence and wavelet features as input to classifier, F. Meng et al. [10] presents an approach for camera source identification with good performance.

In this paper, we propose an effective source camera identification approach by extracting features from wavelet domain which has been proved more significant than the spatial domain [11], and use SFFS to select the most significant features and multi-class SVM as classifier.Comparing to the prior proposed similar passive forensic methods for source camera identification, the identification performance of our proposed scheme is not only highly improved but also can distinguish different types of same Canon brand digital cameras.

The rest of this paper is organized as follows. Section 2 first gives a brief introduction to the imaging pipeline of digital cameras and the framework of the proposed source camera identification approach which is furthermore described in Section 3. Section 4 reports the experiment setup and experimental results. Finally, Conclusions are

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given in Section 5.

## II. IMAGING PIPELINE AND IDENTIFICATION FRAMEWORK

The imaging pipelines of digital cameras are similar, irrespective of manufacturer or model. The basic structure of a digital imaging pipeline is organized as shown in Fig.1. Passing through the whole imaging pipeline, the digital image is stored in the memory in the end according to a user-defined format, such as RAW, TIFF, and JPEG.

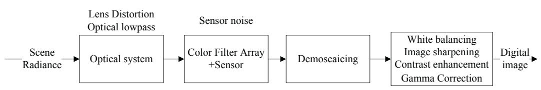


Figure 1. Imaging pipeline in digital cameras

By taking into account of the intrinsic defects and processing of imaging pipeline within digital cameras, we consider the whole imaging pipeline as a black box which result in different features displayed in the output images. Therefore, we have developed a forensic framework which is shown in Fig.2.

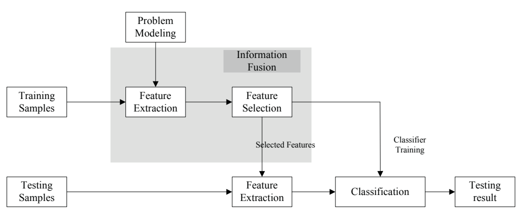


Figure 2. Feature-based source camera identification framework

It includes four main procedures which will be elaborated in the next section: feature extraction, feature analysis and selection, classifier training and identification validation.

## III. WAVELET STATISTIC FEATURES EXTRACTION AND CLASSIFICATION

In this section, we introduce the statistical model for natural photography from the wavelet coefficients including 216 higher-order wavelet features and 135 wavelet coefficient co-occurrence statistics. To reduce the correlation among features and computing load, we use SFFS to select features while keeping the same classification accuracy, at last we apply SVM which acts as classifier.

### A. Wavelet Features Extraction

Instead of using the spatial features (image color and IQM) as in [8] and CFA features as in [6], [7], we choose to extract distinguishable features from the wavelet domain, because the feature comparison results in [11] for features used in [8] tell us that wavelet domain features are the most significant in the identification process, and our experiments further validate this fact. In our identifying scheme, we form the statistical model for natural digital image from the wavelet coefficients including 216 higher-order wavelet features and 135 wavelet coefficient co-occurrence statistics.

*1) Higher-order wavelet features:* Motivated by the effectiveness of wavelet coefficient statistics used in steganalysis [12] and image origin identification [13], the same features are extracted from the wavelet domain as one group of the identification features.

The extraction process of higher-order wavelet features is shown in Fig.3. Four-scale wavelet decomposition is employed based on separable quadrate mirror filters (QMFs) to split the frequency space into four scales and orientations (a vertical, a horizontal, and a diagonal subband). For color images, this decomposition is applied independently to each color channel. Next four statistics (mean, variance, skewness and kurtosis) of the subband coefficient histograms and the linear prediction erros at each orientation, scale and color channel are extracted.

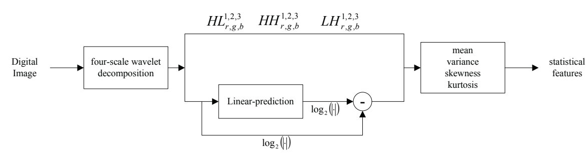


Figure 3. Higher-order wavelet features extraction

For a multi-scale decomposition with scales 4, the total number of basic coefficient statistics and error statistics are both $36 \times (4-1) = 108$,yielding a total of 216 statistics.

*2) Wavelet coefficient co-occurrence statistics:* It has been shown that the wavelet coefficients are highly correlated with each other. This correlation, mainly caused by features such as lines, edges, and corners, arises between coefficients corresponding to different scales and orientations. The 216 statistics mentioned above indeed describe the basic coefficient distributions and furthermore capture the strong correlations existing across space, orientation and scale. However, those features do not concern the texture correlation.

So we also take the texture correlation existing in the wavelet coefficients into consideration. It has been observed that the co-occurrence features are the best among those used in the image texture feature extraction [14]. We use co-occurrence matrix constructed from wavelet coefficients to form image texture representation and apply distance calculation in the same orientation to coefficients of co-occurrence matrix between different scales. Then we extract statistical features from those distances.

The extraction method of wavelet co-occurrence features is shown in Fig.4. We use Db8 four-scale wavelet decomposition and the distances are calculated from the resulting

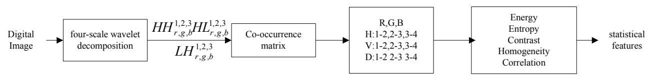


Figure 4. Wavelet co-occurrence features extraction

vertical, horizontal, and diagonal subbands co-occurrence matricesfor each scale and color channel.

Then the energy, entropy, contrast, homogeneity and correlation features from those distances are calculated. Finally we obtain $3 \times 3 \times 3 \times 5 = 135$ statistical features.

### B. Feature Selection and Classification

We use the Sequential Forward Feature Selection (SFFS) algorithm [15] as our feature selection method to reduce the correlation among features and improve the performance of the system. The algorithm provides reliable results at an affordable computational cost. The SFFS method analyzes all the features and constructs the most significant feature set by adding or removing features until no more improvement is available. The steps in the algorithm are as follows:

1. Initialize the current feature vector with the pair of features yielding the best classification result.

2. Add the most significant feature from the remaining ones to the current feature set.

3.Remove the least significant feature from the current selected feature set (the removal of this feature improves the classification result the most).

4. Check if the removal improves or reduces the classification result. If it improves, remove this feature and return to step 3; otherwise do not remove this feature and return to 2.

The multi-class support vector machine (multi-class SVM) [16] is used as classifier after feature selection,. Our experiment use C-support vector classification with the non-linear RBF kernel, in which two tunable parameters "$C$" and "$\gamma$ " are determined by performing a grid search using -fold cross validation [17]. In our experiments, a 5-fold cross validation was performed for each $(C, \gamma)$ pair with values in the set of $\{2^{-5}, 2^{-4}, ..., 2^{5}\}$. The parameter pair with the highest cross-validation accuracy was selected.

## IV. Experimental results

This section describes the experimental setup for testing the source camera identification method and the results that were obtained.

### A. Experiment setup

In our experiments, we use six different cameras with four brands and two models from the same brand (Canon) to investigate the effectiveness of our approach in recognizing different camera models from the same brand.Table I lists the parameters of these cameras together with formats and resolutions of sample images.

Table I
CAMERAS AND SAMPLE IMAGES AND THEIR PROPERTIES

| Cameras | Camera Parameters | | Sample Image Parameters | |
|---|---|---|---|---|
| type | Sensor | Max-Resolution | Image Resolution | Image Format |
| Kodak DC290 | Unspecified CCD | 2240×1500 | 2240×1500 | JPEG |
| Nikon 5700 | 2/3-inch CCD | 2560×1920 | 1600×1200 | JPEG |
| Sony DSC-F828 | 2/3-inch CCD | 3264×2448 | 1280×960 | JPEG |
| Canon PowerShot Pro1 | 2/3-inch CCD | 3264×2448 | 1600×1200 | JPEG |
| Canon PowerShot G2 | 1/1.8-inch CCD | 2272×1704 | 2272×1704;1600×1200;1024×768 | JPEG |
| Canon PowerShot G3 | 1/1.8-inch CCD | 2272×1704 | 2272×1704 | JPEG |

We collected 2100 images as samples from all cameras (350 images for each camera) at auto-focus mode and in JPEG format. The images are typical shots varying from nature scenes to close-ups of people. 1200 of all the samples were used for training and the other 900 images were used for testing. The training and testing samples were selected randomly.

### B. Experimental Evaluation of the Proposed Method

Table II presents the confusion matrix for the average result obtained after computing the image features in Section 3.1 and applying the feature selection and classification method discussed in Section 3.2. Note that using the SFFS method we selected 87 dimension features which are used in the SVM training and testing out of 351.

Table II
EXPERIMENT RESULTS

| Camera | Kodak | Nikon | Sony | CanonPro1 | CanonG2 | CanonG3 | Accuracy |
|---|---|---|---|---|---|---|---|
| **Kodak** | **150** | 0 | 0 | 0 | 0 | 0 | **100%** |
| **Nikon** | 0 | **148** | 0 | 2 | 0 | 0 | **98.7%** |
| **Sony** | 0 | 2 | **148** | 0 | 0 | 0 | **98.7%** |
| **Canon Pro1** | 0 | 0 | 1 | **145** | 4 | 0 | **96.7%** |
| **Canon G2** | 0 | 0 | 0 | 3 | **143** | 4 | **95.3%** |
| **Canon G3** | 0 | 0 | 0 | 0 | 2 | **148** | **98.7%** |

We can observe from the confusion matrix that the average identification accuracy is 98%, and at the same time the accuracy for three Canon cameras also achieves a rate of 96.9%. We also noticed from the experiment results that the identification accuracy of Canon Powershot G2 is the lowest. The reason is that image samples from Canon Powershot G2 include three kinds of resolutions, and we can draw the conclusion that the diversity of resolutions of image samples has some influence on the identification accuracy.

The experimental results of the comparison between the proposed method and Kharrazi's method [8], using the same image samples, are given in Fig.10. One can observe that the average accuracy of Kharrazi's scheme is about 90.9%, however distinguishing performance of Canon Pro1 and CanonG2 only close to 85.3% and 84.7% respectively.

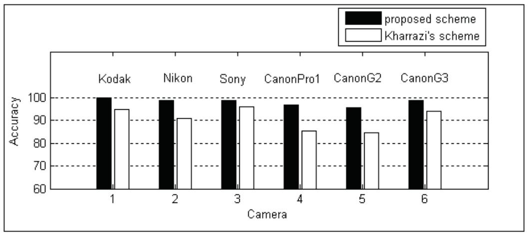


Figure 5. Comparison results between the proposed scheme and Kharrazi's scheme

From the comparison results in Fig.5, we can conclude that the use of the proposed identification framework greatly improves the distinguishing accuracy, especially for cameras by the same brand but with different models. Our method thus makes obvious improvements to the reliability of source camera identification.

## V. Conclusion and future work

The source camera identification method, which engages statistical characteristics of higher-order wavelet features and wavelet coefficient co-occurrence features as distinguishing features, the sequential forward feature selection algorithm for feature selection and a support vector machine for classification, is both efficient and reliable.

In contrast with the method of Kharrazi et al. [8], there is prominent improvement on the distinguishing ability especially for cameras by same brand but with different models. Moreover, there is no rigorous need to constrain the image samples unlike the approach by Kai San Choi et al.

Our future plans include improving the proposed feature vector, evaluating the robustness of the identification system, considering other kinds of pattern classification methods such as clustering as in [18] or one-class SVM and enlarging the image dataset so that the images available from each camera model cover a large range of texture and content.

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