Computing
DOI 10.1007/s00607-013-0313-5

Source identification for mobile devices, based on wavelet transforms combined with sensor imperfections

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Received: 22 January 2013 / Accepted: 11 February 2013

Abstract One of the most relevant applications of digital image forensics is to accurately identify the device used for taking a given set of images, a problem called source identification. This paper studies recent developments in the field and proposes the mixture of two techniques (Sensor Imperfections and Wavelet Transforms) to get better source identification of images generated with mobile devices. Our results show that Sensor Imperfections and Wavelet Transforms can jointly serve as good forensic features to help trace the source camera of images produced by mobile phones. Furthermore, the model proposed here can also determine with high precision both the brand and model of the device.

Keywords Image forensics · Source model identification · Classification · Wavelet · Sensor imperfection · Support vector machines (SVMs)

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1 Introduction

Source identification research investigates techniques to identify the characteristics of digital data acquisition devices (*e.g.*, digital cameras and mobile phones) used in the generation of images. These techniques are expected to achieve two major outcomes. The first is to infer the class (model) of the source, the second is to accurately find its individual source properties. The success of source identification techniques depend on the assumption that all images acquired by the same image acquisition device will exhibit certain characteristics that are intrinsic to it, 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 despite the fact that they frequently encode device related information (like model, type, date and time, and compression details in the image header, *e.g.*, EXIF header) this information can be easily tampered with, so it cannot be used for forensics purposes.

1.1 Image formation in digital cameras

The design of image source identification techniques requires a basic understanding of the physics in operation on these devices. The general structure of the image formation pipeline remains similar for almost all digital cameras, although much of the details are kept as proprietary information by each manufacturer. The basic structure is illustrated in Fig. 1.

Consumer level digital cameras consist of a lens system, sampling filters, a color filter array, imaging sensor, and a digital image processor [1]. The lens system is

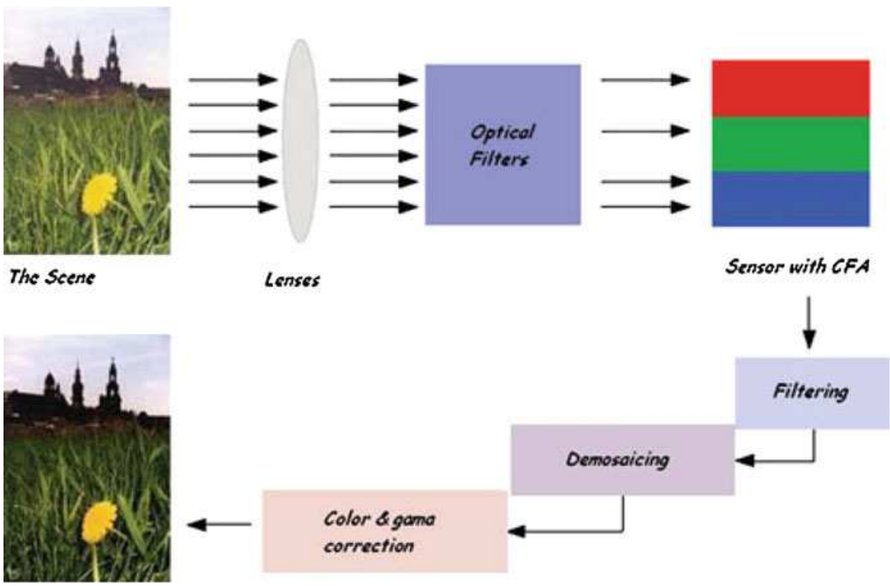

Fig. 1 Stages of digital camera pipeline [1]

essentially composed of a lens and the mechanisms to control exposure, focus, 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 the imaging sensor, an array of light-sensing elements called pixels. Digital cameras generally employ charge-coupled device (CCD) or complimentary metal-oxide semiconductor (CMOS) imaging sensors. Each light sensing element of the 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 color images requires separate sensors for each color component. However, due to cost considerations in most digital cameras only a single sensor is used along with a color filter array (CFA). The CFA arranges pixels in a pattern so that each element has a different spectral filter. Hence, each element only detects one wavelength band, and the raw image collected from the imaging sensor is a mosaic of different colors and varying intensity values. The CFA patterns are generally comprised of red-green-blue (RGB) and cyan-magenta-yellow (CMY) color components. The measured color 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 provides information about a number of color component values, the missing one 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 in a digital camera, the exact details in each stage varies from one manufacturer to another, and even in different camera models by the same manufacturer.

2 Source model identification

The features used to differentiate camera-models are derived from differences in processing techniques, and the component technologies. The major problem with this approach is that many different models and brands use components by only a few number of manufacturers, and the processing steps and algorithms remain in general very similar among different models of a brand. Hence, reliable identification of a source camera-model heavily depends on characterizations of various model-dependent features as briefly explained below.

2.1 Techniques based on metadata

These are the simplest, although they strongly depend on the data the maker decides to insert as metadata when the picture is taken. Furthermore, this method is the most vulnerable to tampering. Nevertheless, if it can be shown by any means that there were not any external modifications, using the generally large amount of metadata present can greatly help the forensic analyst.

There is a huge number of works focusing on the different types of metadata in pictures, for search and classification purposes [2,3,16,17]. As stated before, these techniques, though simplest, depend on the quality and quantity of metadata the maker decides to introduce. The most widespread specification to identify the source of the camera, Exif [15], has two specific tags: "Make" and "Model". Unfortunately, filling data in those tags is not mandatory.

2.2 Techniques based on image features

Çeliktutan et al. [4] use a set of binary similarity measures for assessing the similitude between the bit-planes of an image. The underlying assumption is that proprietary CFA interpolation algorithms leave correlations across adjacent bit-planes of an image that can be captured by the proposed measures. 108 binary similarity measures are obtained for image classification purposes. The results of their experiment for a group of 9 cameras has accuracy 62 %, collecting 200 images from each of the maximum resolutions, with a constant size of 640×480 pixels, at day light, and in auto-focus mode.

Tsai et al. [18] proposed different methods: They used a set of image features to obtain camera characteristics. These include color features, quality features and image characteristics in the frequency domain. They adopt the Wavelet Transform method for computing wavelet domain statistics, and added SVM to the search stage to enhance the identification rate. The results obtained over four camera models from two different brands yielded average accuracies close to 92 %.

McKay et al. [10] extend the image source identification technique to devices such as mobile phone cameras, digital cameras, and scanners. To achieve this, they first should find sources of variation among different devices, and between different models of a device. They use the dissimilarities in the image acquisition process to develop two groups of features, namely color interpolation coefficients and noise features. They later use these to obtain an accurate identification. In their experiments they employed five different models of mobile phones, five models of digital cameras and four models of scanner to identify the source type. The results were an overall identification accuracy of 93.75 %. In their analysis of the identifying device brand/model of the smartphone, they obtained an accuracy close to 97.7 % for five models.

2.3 Techniques based on CFA and demosaicing artifacts

The choice of CFA and the specifics of the demosacing algorithm produce some of the most pronounced differences among different digital camera models. In those with a single imaging sensor, the use of demosacing algorithms is crucial for correct rendering high spatial image details, and it greatly impacts the edge and color quality of an image. Essentially, demosaicing is a form of interpolation which in effect introduces a specific type of inter-dependency (correlations) between the color values of image pixels. The specific form of these dependencies can be extracted from the images to fingerprint different demosaicing algorithms, and to determine the source camera-model of an image. Brayman et al. [1], describe their approach to identify, detect and classify traces of demosaicing operations. They rely on two methods: The first is based on the use of Expectation-Maximization algorithms which analyze the correlation of each pixel value to its neighbours; The second method is based on analyzing inter-pixel differences. They divide their experiments into two categories. The first category was performed to asses the accuracy of camera-model identification, and the second evaluated the improvement in individual camera identification. The accuracy in identifying the source of an image among four and five models is measured as 88 and 84.8 %, respectively, using images captured under automatic settings and at highest compression levels.

2.4 Techniques based on the use of sensor imperfections

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

Geradts et al. [7] examine CCD pixel defects, but this work is not very relevant in our case as we are dealing with CMOS. This technique includes point defects, hot points, dead pixels, pixel traps and cluster defects. The result noted that each of the cameras had a different defect pattern. Nevertheless, it also showed that the number of defects in the pixels for a camera differed between pictures and varies quite significantly depending on the content of the image. It also revealed that the number of defects varied at different temperatures. Finally, the study found that cameras with high-end CCDs did not generally had this kind of problem, thus not all cameras suffered from this issue. It is also true that most cameras have additional mechanisms to compensate for this problem.

Luka et al. [9] proposes 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 and allows identifying the sensors and therefore the camera. The result for pictures of different sizes and for cropped images is, unfortunately, not satisfactory [19].

2.5 Techniques based on wavelet transforms

Meng et al. [11] 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, the 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 statistical features.

Next, 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 sub-band coefficients and the linear prediction errors at each orientation, scale and color 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 [13] is used to reduce the correlation among features and computing load, while keeping the same classification accuracy. The SFFS method analyzes all the features and builds the most significant set from them by adding and removing features until no more improvements are possible.

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

The results obtained from this technique are satisfactory, based on their success in distinguishing different cameras of the same brand. However, further improvements could be made by incorporating features from other techniques like in the next approach.

The work in [20] describes a scheme for source camera identification based on extracting and classifying wavelet statistical features. This method is composed of three phases: Wavelet Feature Extraction, Wavelet Feature Selection, and Wavelet Feature Classification.

Outstanding features from the wavelet 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. Features from the wavelet domain are preferred over spatial features (image color and Image Quality Metrics IQM) and Color Filter Array (CFA).

Analogously to the aforementioned forementioned 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 relate to the texture correlation, as it has been observed the co-occurrence features are the best among those used in the image texture feature extraction [14]. 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 features selection and classification processes are performed in the same manner as in the above method, using the SFFS algorithm to select the most representative features, and a multi-class SVM as classifier.

As in the previous experiments, they succeeded in distinguishing different types of the same Canon camera. However, this could be improved 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 [12] exposes a differentiating images technique using transforms from the wavelet family. They propose statistical models for ridge-let, and contour-let sub-bands.

– *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, a system called “ridgelets” was devel-

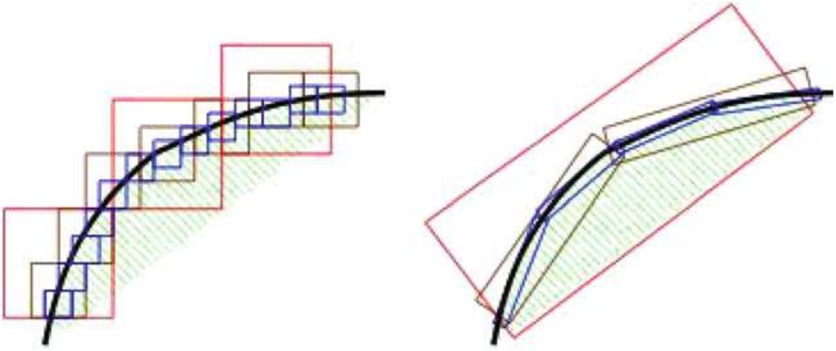

Fig. 2 Wavelet representation versus contourlet representation [6]

oped. 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.

– *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 (Fig. 2a). Likewise, the representation called "contourlets" [6] is the equivalent to using contour lines, simplifying the image construction and giving it a realistic appearance (Fig. 2a).

According to the results of previous studies [6], an efficient representation of an image should satisfy the following characteristics:

1. *Multi-resolution*: The representation must be a successful approximation to 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. As final steps, sequential floating search (SFS) for the feature selection is applied and a SVM 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).

Studies on wavelet techniques have produced positive results. Nonetheless, we propose in here their usage for mobile phone cameras. This deserves special mention owing to the fact that the experiments have been focused on traditional cameras leaving out one of the fields that currently is gaining more ground every day.

3 Proposal description

In this section, we describe how features extracted can be utilized to more reliably detect the individual source camera of an image. Here the two types of methods (sensor imperfections and wavelet transforms) are combined to more accurately detect source camera of an image.

3.1 Sensor noise patterns

During the image generation process, usually several defects are injected; these will appear in the final image as noise. One type of noise is caused by array's defects; this includes hot point defects, dead pixels, pixel traps, cluster defects, and column defects. This causes those pixels to differ greatly from the original image, in several cases being indifferent to which of the two images is taken, since they all the time show the same pixel value. For instance, the dead pixels will appear in the image as a black pixel in the resulting image, and hot pixels will appear as brilliant points. The noise pattern in an image refers to any spatial pattern that does not change between images and it is generated by a "*dark current*" and PRNU (photoresponse non uniformity) [8].

There are some filters to smooth out the effect of this noise. For simplicity, speed and ease of implementation we will use the Gaussian filter. This filter will be used later to eliminate quickly and effectively the noise in the images, and with these data we will be able to perform different operations that lead us to determine the different features.

Our aim is to obtain a set of image features that enable us to clearly differentiate the camera model.

Given an initial image of $M * N$ pixels, whith M rows and N columns, we denote I_{noise} as the noise in the original image and $I_{denoised}$ as the image with no noise. Then we get:

$$I_{noise} = I - I_{denoised}$$

In order to achieve noise-free images we will use the Gaussian filter, which provides us the necessary speed for analyzing large numbers of photos in a short time. Next, we will subtract each color component (RGB) to the original picture, which will give the noise component of each pixel for each color.

The noise in the original image I_{noise} can be modelled as the sum of two components, the constant noise $I_{noiseconstant}$ and random noise $I_{noiserandom}$.

$$\hat{I}_{noiseconstant}(1, j) = \frac{\sum_{i=1}^{M} I_{noise}(i, j)}{M}, 1 \leq j \leq N$$

To identify the similarities between different rows regarding the reference pattern, we will use the correlation of these with the mentioned pattern.

$$correlation(X, Y) = \frac{\left(X - \overline{X}\right) \cdot \left(Y - \overline{Y}\right)}{\left\| X - \overline{X} \right\| \cdot \left\| Y - \overline{Y} \right\|}$$

We do the same for columns.

Once we obtain the row and column correlations, we will extract the features.

At the time of obtaining the features it is important to consider that the input image orientation is critical, as this might change completely the resulting features.

3.2 First-order and higher-order features

For every type of correlation (rows or columns) we obtain the first-order statistics: mean, median, minimum and maximum. The higher-order features are: variance, skewness and kurtosis. Additionally, we add the ratio between the correlations of rows and columns.

It was considered appropriate adding a new feature based on the image noise to the set of features above. This new feature measures the medium noise per pixel, which is independent from the columns and rows correlations of the reference pattern.

In total we have seven rows features, seven columns features, the ratio and average pixel noise, resulting in a total of 16 features.

3.3 Wavelet transforms

Each color band is split into three sub-bands using QMFs (*separable quadratic mirror filters*) and subsequently the mean of each of the three sub bands, giving us a total of 9 features.

In Fig. 3 the absolute values of the coefficients of the sub-bands for a disk image are shown. It can be observed the top right sub-band vertical, the bottom left diagonal sub-band, and the bottom left diagonal subband. This image shows three-level decomposition, our algorithm uses just one level.

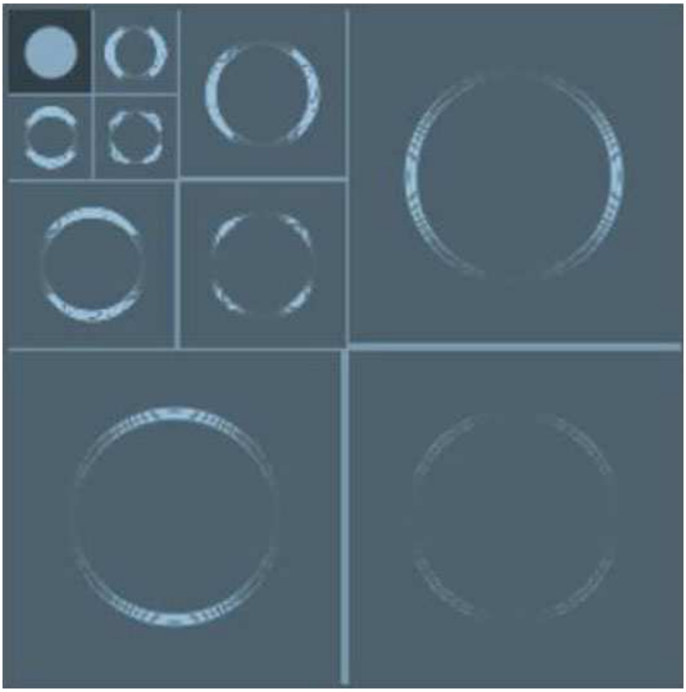

Fig. 3 Example wavelet sub-bands

4 Support vector machine-based classification

SVM algorithms belong to the lineal classifiers family. In this type of classifiers there is a priori knowledge about the classes at which the individuals that we want classify belong [5].

Given a set of training examples (samples) we can label classes and train a SVM to build a model that predicts the class of a new sample. Intuitively, an SVM is a model representing the sample points in the space, separating the classes by a space as wide as possible. When new samples are placed in correspondence with the established pattern, depending on their proximity they may be classified into one class depending on the proximity to each one.

Formally, a SMV generates an hyperplane or an hyperplane set in a high dimensional space which can be used in classifying or regression problems. An efficient separation between classes allows more accurate classification.

Mathematically:

Starting from a set of training data $\{x_i, y_i\}$ with:

$$i = 1, \dots, l,\ y_i \in \{-1, 1\}\ \text{y}\ x_i \in R^d$$

Then there exists a hyperplane which separates data from positive and negative labels, such that:

$$x_i\omega + b \geq 1 - \xi_i\, paray_i = 1 x_i\omega + b \leq 1 + \xi_i\, paray_i = -1 x_i \geq \forall i$$

Where ω is the normal to the hyperplane and x_i are the variables introduced by classification errors as violations of the hyperplane, so $\sum \xi_i$ will be the classification error bound. A straightforward way to add the objective function cost is to minimize $\frac{\|\omega^2\|}{2} + C\sum \xi_i$, being C the constant chosen for the inverse of the value of the criminalization of errors. Thus, we have a convex optimization problem whose quadratic optimization is the number of support vectors.

In most cases, the input space is not linear, so that a transformation needs to be done to a Euclidean space H.

Therefore, the training algorithm depends only on the data input through the products of the form $\phi(x_i) : \phi(x_j)$. Then there exists a function called "kernel" such that is true that:

$$K(x_i, x_j) = \phi(x_i) : \phi(x_j)$$

Among "kernels" the most commonly used are:

- Polynomial (homogeneous) $K(x_i, x_j) = (x_i \cdot x_j)^d$
- Polynomial (heterogeneous) $K(x_i, x_j) = (x_i \cdot x_j + 1)^d$
- RBF (Radial Basis Function) $K(x_i, x_j) = exp\left(-\gamma \|x_i - x_j\|^2\right)$
- Hyperbolic tangent $K(x_i, x_j) = tanh(kx_i \cdot x_j + c)$ for $k > 0$ y $c < 0$

5 Experiments and results

To verify the effectiveness of our extraction features algorithm for identifying different sources, several experiments were made varying the mobile phone models and the number of pictures, as we will also take into account how this affects the algorithm. At least 30 pictures of each mobile were taken. In our first experiment, we will use 10 different phone models and various brands which are listed below: Iphone 3G, Iphone 3GS, Blackberry 8520, HTC Desire HD, LG Ku990i, Nokia 5300, Nokia 6110, Nokia N95, Nokia E61i, Sony and Ericsson W580i.

Of all these models we take exactly 50 photographs.

The results show a 89.4 % accuracy. With so few photographs of each group, the result seems quite remarkable.

We took another group of phones, from which there will be at least 150 photos with a maximum of 200. The seven considered models are: Blackberry 8520, HTC Desire HD, LG Ku990i, Nokia 5300, Nokia 6110, Nokia 6300, Sony Ericsson T707, and Sony Ericsson W580i.

The result in this case is a 94.2 % accuracy. Therefore, we can observe that the performance of the algorithm is much better as a consequence of having more images, but is also positively affected because we have three models less.

With the propose of making a more direct comparison of how the number of classes affects performance, we will compare two common models, five groups in total with

Table 1 Accuracy rate by number of images

Number of images	Success rate (%)
30	96.6
60	95
90	94.4
120	96.6
150	96.3

50 pictures each, and then we will try with 150 photos each. The common models of each brand are: Blackberry 8520, HTC Desire HD,LG Ku990i, Nokia 5300, and Sony Ericsson W580i.

For 50 images we have an accuracy of 95.8 %. With 100 images each we have a rate of 96.2 %. We can see that the difference is not huge, and probably not statistically significant. We tested only two groups to verify if this difference could be even smaller, and so we used the Blackberry 8520 and Sony Ericsson W580i.

Table 1 shows that the accuracy does not change significantly, so we can conclude that the number of images does not affect significantly the success rate in this approach.

6 Conclusions

This paper studies the recent developments in the field of image source identification. Proposed techniques in the literature are categorized into five main areas based on source model identification: Metadata, Image Features, CFA and Demosaicing Artifacts, 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.

Furthermore, we present our approach for image acquisition forensics to identify both the type of image acquisition device and the brand/model of the device. We have proposed to jointly employ sensor imperfections and wavelet transforms as features for forensic analysis. These are estimated from the images and are jointly used as features for forensic analysis. We show that the combined set of features can provide tell-tale clues and accurately help trace the origin of the input image and help identify the mobile phone camera brand and model that was used in its capture with high accuracy. Our approach utilizes the optimal parameter search from SVM for prediction and classification, which results in a better identification rate.

Acknowledgments This work was supported by the Agencia Española de Cooperación Internacional para el Desarrollo (AECID, Spain) through Acción Integrada MAEC-AECID MEDITERRÁNEO A1/037528/11.

References

1. Bayram S, Sencar HT, Memon N (2008) Classification of digital camera-models based on demosaicing artifacts. Digit Investig 5(1–2):49–59
2. Boutell M, Luo, J (2004) Photo classification by integrating image content and camera metadata. In: Proceedings of the 17th international conference on pattern recognition, vol 4. IEEE Computer Society, pp 901–904. doi:10.1109/ICPR.2004.1333918

3. Boutell M, Luo J (2005) Beyond pixels: exploiting camera metadata for photo classification. Pattern Recogn 38(6):935–946. doi:10.1016/j.patcog.2004.11.013
4. Celiktutan O, Avcibas I, Sankur B, Ayerden NP, Capar C (2006) Source cell-phone identification. In: 2006 IEEE 14th signal processing and communications applications, pp 1–3. doi:10.1109/SIU.2006.1659882
5. Chang C, Lin C (2001) LIBSVM: A library for support vector machines. Tech. rep. Software available at: http://www.csie.ntu.edu.tw/cjlin/libsvm
6. Do MN, Vetterli M (2005) The contourlet transform: an efficient directional multiresolution image representation. IEEE Trans Image Process 14(12):2091–2106
7. Geradts ZJ, Bijhold J, Kieft M, Kurosawa K, Kuroki K, Saitoh N (2001) Methods for identification of images acquired with digital cameras. In: Proceedings of the SPIE, vol 4232. Spie, pp 505–512. doi:10.1117/12.417569
8. Khannaa N, Mikkilinenib AK, Chiub GT, Allebacha JP, Delpa EJ (2006) Forensic classification of imaging sensor types. In: Rfc. Purdue University, USA
9. Luka J, Fridrich J, Goljan M (2006) Digital camera identification from sensor pattern noise. IEEE Trans Inform Forensics Security 1(2):205–214. doi:10.1109/TIFS.2006.873602
10. Mckay C, Swaminathan A, Gou H, Wu M (2008) Image acquisition forensics: forensic analysis to identify imaging source. In: IEEE international conference on acoustics speech and, signal processing, pp 1657–1660. doi:10.1109/ICASSP.2008.4517945
11. Meng FJ, Kong XW, You XG (2008) Source camera identification based on image bi-coherence and wavelet features. In: Proceedings of the fourth annual IFIP WG 11.9 international conference on digital forensics. Kyoto, Japan
12. Ozparlak L, Avcibas I (2011) Differentiating between images using wavelet-based transforms: a comparative study. IEEE Trans Inform Forensics Security 6(4):1418–1431
13. Pudil P, Novovičová J, Kittler J (1994) Floating search methods in feature selection. Pattern Recogn Lett 15(11):1119–1125
14. Randen T, Husøy JH (1999) Filtering for texture classification: a comparative study. IEEE Trans Pattern Anal Mach Intell 21(4):291–310
15. Baer R (2010) Resolution limits in digital photography: the looming end of the pixel wars - OSA technical digest (CD). In: Proceedings of the imaging systems. Optical Society of America, p ITuB3
16. Romero NL, Chornet VG, Cobos JS, Carot AS, Centellas FC, Mendez MC (2008) Recovery of descriptive information in images from digital libraries by means of EXIF metadata. Library Hi Tech 26(2):302–315. doi:10.1108/07378830810880388
17. Tesic J (2005) Metadata practices for consumer photos. IEEE Multimed 12(3):86–92. doi:10.1109/MMUL.2005.50
18. Tsai MJ, Lai CL, Liu J (2007) Camera/mobile phone source identification for digital forensics. In: Proceedings of the IEEE international conference on acoustics speech and signal processing ICASSP 07, pp II-221-II-224
19. Van Lanh T, Chong KS, Emmanuel S, Kankanhalli MS (2007) A survey on digital camera image forensic methods. IEEE Int Conf Multimed Expo 2007:16–19. doi:10.1109/ICME.2007.4284575
20. Wang B, Guo Y, Kong X, Meng F (2009) Source camera identification forensics based on wavelet features. In: Proceedings of the international conference on intelligent information hiding and multimedia signal processing, vol 0. IEEE Computer Society, Los Alamitos, pp 702–705