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Inter-Camera Model Image Source Identification with Conditional Probability Features

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***Abstract*—In this paper, we propose a camera identification algorithm based on the conditional probability features (called CP features in this paper). Specifically, we report its performance for identification of image sources. Using four cameras of different models, we demonstrate that the CP features allow us to correctly identify the sources of 400 test images with an average accuracy of 99.50%. Additionally, the CP features based camera identification algorithm is also robust to cropping and compression. When the 400 images are cropped and JPEG compressed with QF=80 the average identification accuracy only slightly drops to 97.75%. These experimental results provide a good indication that CP features are promising new features for image forensics purposes.**

I. Introduction

Digital images are widely used in today's society due to the availability of a wide range of affordable digital cameras with different specifications and functions. Furthermore, the popularity of mobile phones equipped with image capturing capability such as the Apple iPhone contributes further to the generation, transmission and storage of digital images.

Digital images are being more frequently exhibited either directly or indirectly in court as an evidence for law enforcement [1]. However, the manipulation of digital images is made simple with easily available image processing tools, making it harder to trust them. An obvious example related to the contents of file headers has been pointed out in [2]. For instance, Exchangeable Image File (EXIF) header data may contain information such as digital camera type, time taken and exposure. However, this information may not be present if, for example, the image is re-saved to a different file format. What's even worse, information in file headers can be deliberately modified. Figure 1 shows the graphical GUI of a software packages called *ExifTool* [3] that allows manipulation of EXIF file headers.

This is where digital forensics becomes important: to ensure the integrity of the digital evidence is guaranteed. Digital forensics helps by extracting more essential information about an image from the surface, such as the source of the image, i.e. the imaging device (camera) through which the image was produced. This digital forensics problem is known as "camera identification".

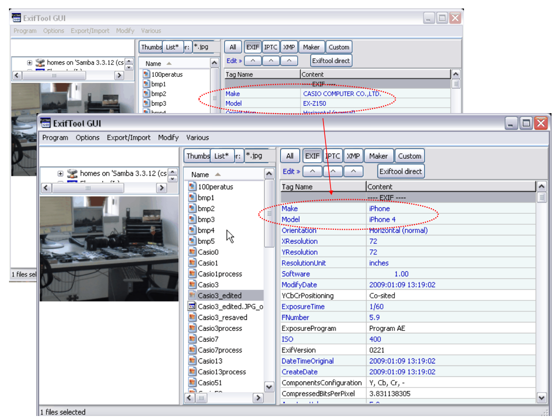

Fig. 1. "Make" and "Model" fields in an EXIF file header changed by *ExifTool* software package [3].

II. Related Work

Much research has focused on the identification of a unique signature that can link an image to its source camera. For example, in an early work on camera identification [4] the signature is composed of 34 features extracted from the image represented in spatial and wavelet domains, where the wavelet domain features are based on features introduced in another earlier work of Farid [5]. This method could achieve a detection accuracy between 78% and 95%.

Another approach proposed in [6] employs *statistical process control* (SPC) charts on image variations. In this paper, the charts act as a tool to detect anomalies in image data. The statistical differences provide a fingerprint to relate the image with the source device. The authors of [6] found a clear distinction between images from low-end cameras, where the variation was approximately 21%, and mid-range ones, where the variation was only around 1%.

In [2], camera sensors were shown to produce specific noise patterns that could result in unique signatures. Li later demonstrated [7] that the sensor pattern noises extracted from images can be severely contaminated by details from scenes. To deal with this issue, Li proposed a novel approach for reducing the influence by assigning weighting factors inversely proportional to the magnitude of the sensor pattern noise components. A maximum improvement of 18% on true positive rate was delivered with the smallest photo size (128×128) while the minimum improvement of 1% achieved on the biggest photo size (1536×2048).

In [8] Gloe *et al.* defined two types of experiments related to camera identification: the *inter-camera* model and the *intra-camera* model classification. The *inter-camera* model classification considers images taken by cameras of different brands or models, while, the *intra-camera* model classification examines images from the same brand and model cameras. In this paper, we are working with the first category of camera identification experiments, the inter-camera model case.

III. CP Features

Wahab et al. have proposed to use CP features for steganalysis purpose in [9]. Following that, Wahab and Bateman used CP features for intra-camera model identification in [10]. By examining 400 images captured with four different iPhone cameras, an average accuracy of 92.5% were achieved for this intra-camera model identification case. In this paper we extend the use of CP features for the inter-camera model case. In the following we give the background of CP features and explain how they are extracted from an image.

The revised probability of an event *B* when it is known that another event *A* has occurred is called the conditional probability of *B* given *A* [11]. It is defined as follows:

$$P(B \mid A) = \frac{P(AB)}{P(A)}. \tag{1}$$

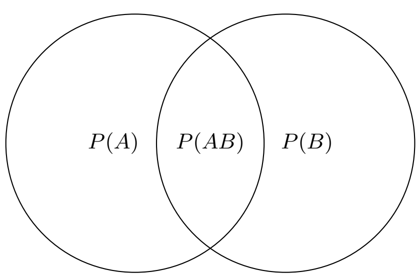

Fig. 2. Venn diagram illustrates $P(A), P(B)$, and $P(AB)$

Figure 2 illustrates $P(A), P(B)$ and $P(AB)$ using a Venn diagram. Based on the concept of conditional probability, a number of CP features can be obtained by examining absolute values of three selected blockwise DCT coefficients at different locations: p, q and r. For the normal 8×8 DCT transform, we picked the three DCT coefficients from the 4×4 left upper sub-block because most non-zero coefficients are in that region. Figure 3 shows eight different selections (or orientations) of the three DCT coefficients in the 4×4 sub-block. Given a particular selection of q, q and r, three *A*-events and three *B*-events are defined as follows:

$$A_1 : p < q, \; A_2 : p > q, \; A_3 : p = q, \tag{2}$$

$$B_1 : r < q, \; B_2 : r > q, \; B_3 : r = q. \tag{3}$$

If we combine each *A*-event and each *B*-event, we can get nine different conditional probabilities that are CP features used for camera identification. Given the eight orientations shown in Figure 3, we have in total 72 CP features.

In previous works [9], [10], only the first three orientations in Figure 3 were used to generate the CP features. In this paper we add five new orientations in order to handle the more complicated inter-camera model case.

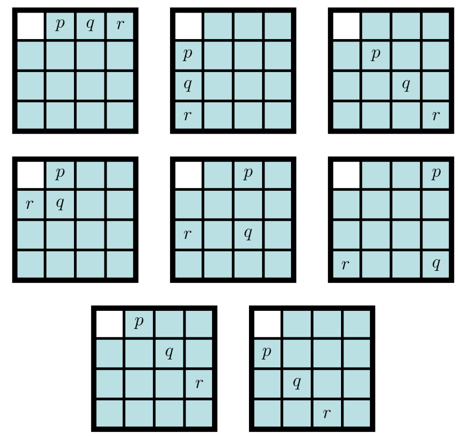

Fig. 3. The eight orientations of p, q and r for generating CP features.

IV. Experimental Setup

A common benchmark is important to allow reproduction of results and fair comparison of different algorithms. Recently, Gloe and Böhme [12] created the Dresden Image Database as a common benchmark dataset for digital image forensics research. It is freely available online at http://forensics.inf.tu-dresden.de/dresden_image_database. The Dresden Image Database contains over 14,000 images captured by 73 different camera models. It includes natural and urban scenes as well as indoor and outdoor images. Despite being a very recent release, it has been used in several recent works on image forensics [13]–[16]. Adding up this list of usage, we decided to work with images taken from the *Dresden Image Database* as well.

To evaluate the performance of CP features for camera identification, a subset of images was selected from the Dresden Image Database and are kept at their original size and format (JPEG). This subset includes images taken by three consumer-level digital cameras and one digital single-lens reflex (SLR) semi-professional camera as shown in Table I.

TABLE I
Four cameras used to capture the subset of images examined in this paper, as stated in the Dresden Image Database.

Brand	Model	Pixel Resolution
Casio	EXILIM Zoom EX-Z150	3264×2448
Kodak	EASYSHARE M1063	3664×2748
Nikon	Coolpix S710	4352×3264
Nikon	D200	2872×2592

In our experiments, the CP features were extracted from the selected images for a subsequent classification process using a support vector machine (SVM) classifier. There are a number of SVM implementations available such as Gist [17], SVM^{light} [18] and LIBSVM [19]. Among them, the LIBSVM classifier was selected due to its ease of use.

V. Experimental Results on Original Images

To see how different the CP features extracted from images taken by different cameras are, we examined the average value of each CP feature extracted from all images taken by each camera. For each camera we have a vector of 72 average values, which are shown in Figure 4, where "NikonS" and "NikonD" denote Nikon Coolpix S710 and Nikon D200, respectively. Furthermore, we define a new vector called *average absolute difference* $\mathbf{\Delta}_{aad}$ to reflect the difference between two randomly selected cameras. Denoting the 72-element vectors of the four cameras by $\mathbf{CP}_i$, $i = 1, 2, 3, 4$,

$$\mathbf{\Delta}_{aad} = \frac{\sum_{i \neq j} |\mathbf{CP}_i - \mathbf{CP}_j|}{6}. \tag{4}$$

For the selected images in our experiments, $\mathbf{\Delta}_{aad}$ ranges from 0.0074 to 0.2738, its mean is 0.0592 and its variance is 0.0056.

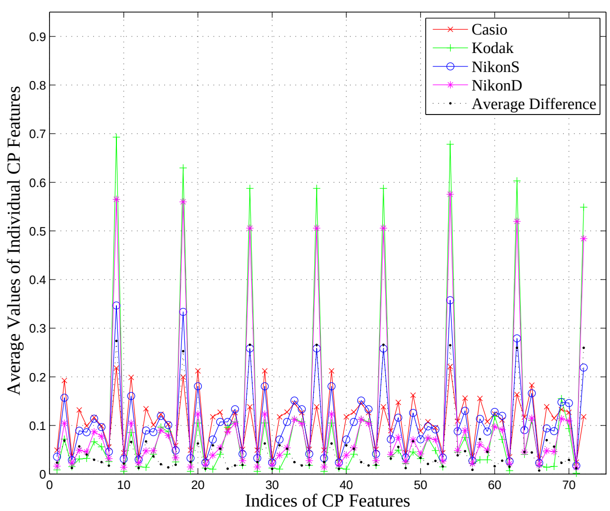

Fig. 4. The average values of all CP features across all images taken by each camera, and the average absolute difference as defined in Eq. (4).

Figure 4 shows a clear difference between any two cameras' curves, i.e., each camera yields a unique pattern of CP features that can be used as a signature. This can be explained by the difference in the image capturing and post-processing pipeline of each camera. For example, we noticed that a different quantisation table was used by each camera to produce the images we tested in our experiments. When a different quantisation table is used in the quantisation process of JPEG compression, it is reasonable to assume that a statistical difference can be produced in the quantised DCT coefficients. This statistical difference can then be captured by the CP features defined in this paper. In addition, the colour interpolation[1] process can also cause a statistical difference in blockwise DCT coefficients as discussed by Long *et al.* in [20]. It is likely that many other steps of the image capturing-processing pipeline can also add further differences to the CP features extracted from the final formed JPEG images.

[1]Colour interpolation is the process of interpolating missing samples of a colour channel of a pixel value from its neighbouring samples of the same colour channel. This is needed for most digital cameras because at each position only one colour sample is taken (so two others are missing).

TABLE II
The confusion matrix and the average classification accuracy for 10 independent tests on a subset of images taken from Dresden Image Database.

	Identified			
	Casio	Kodak	NikonS	NikonD
Casio	99%	0%	0%	1%
Kodak	0%	100%	0%	0%
NikonS	0%	0%	99%	1%
NikonD	0%	0%	0%	100%
Average	**99.5%**			

We ran 10 independent tests to study the performance of the CP features based method. In our experiments, we used 90 randomly selected images per camera model as the training set and 10 the other ones as the testing set, thus in total we have $10 \times 10 = 100$ testing images per camera model and 400 images for the four camera models under study. Table II shows the confusion matrix of the identification results, where each row represents the 100 testing images originating from a particular camera and each column represents the "identified" camera. From the results, one can see that the CP features allow us to identify the sources of the tested images with an average accuracy of 99.50%.

VI. Experimental Results on Processed Images

In previous section we have shown that CP features can be used for camera identification of the original images in the Dresden Image Database. In this section, we further study if the results still hold when the original images are further processed. There are different types of processes that may be applied such as scaling, rotation, cropping and lossy compression. In this paper, we focus on cropping and JPEG re-compression.

In our experiments, we cropped each image into half of its original size followed by JPEG compression with QF=80. Indeed, we intended to use the same QF value for all images to ensure the same quantisation table being used for all images under examination. Figure 5 illustrates the average values of CP features extracted from the processed images taken by each camera. Comparing Fig. 5 with Fig. 4, one can see that the average values associated with the original images have been suppressed by cropping and JPEG re-compressing. This pattern holds for all the four cameras, although the degree of suppression differs. Accordingly, the mean of $\mathbf{\Delta}_{aad}$ decreased from 0.0592 to 0.0141, the standard deviation decreased from 0.0056 to 0.00032921, implying a reduced distinguishability among different cameras. As a result, we expected that the performance of the CP features would be compromised by cropping and lossy JPEG re-compression.

Table III shows the confusion matrix for 10 independent tests. From the results one can see that the average accuracy

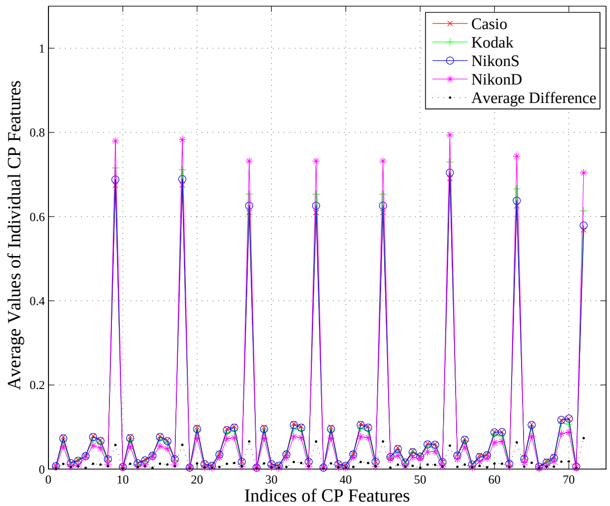

Fig. 5. The average values of all CP features across all processed images whose original editions were taken by each camera, and the corresponding average absolute difference as defined in Eq. (4).

indeed decreased from 99.50% to 97.75%. Although there is a decrease in the average classification accuracy, it is just a small drop so the performance of the CP features based camera identification method is still fairly good. This fact implies that CP features indeed have some robustness to image distortions such as cropping and compression tested in our experiments.

TABLE III
THE CONFUSION MATRIX AND THE AVERAGE CLASSIFICATION ACCURACY FOR 10 INDEPENDENT TESTS ON CP FEATURES EXTRACTED FROM PROCESSED IMAGES.

	Predicted			
	Casio	Kodak	NikonS	NikonD
Casio	97%	0%	3%	0%
Kodak	0%	99%	0%	1%
NikonS	1%	0%	98%	1%
NikonD	0%	1%	2%	97%
Average	**97.75%**			

VII. CONCLUSION

We have develop a new approach to the problem of inter-camera model identification from images by exploiting the conditional probabilities of selected blockwise DCT coefficients. We investigated the reliability of those conditional probability (CP) features for identifying four source cameras that were used to produce some images in the Dresden Image Database. Images processed by cropping and lossy JPEG re-compression were also investigated. Our experimental results showed that the CP features can lead to a very good identification accuracy for both original and processed images.

In future work, we plan to further apply the CP features based method to a larger set of images covering a large range of texture and scenery and a large number of camera models. Another research direction is to study if CP features can also work in other transform domains like DWT. Conditional probabilities cross different colour channels may also be considered to further improve the performance of camera identification based on CP features. Yet another topic for further study is if other selections of the three DCT coefficients p, q and r will help further improve the performance of the identification results. It is possible that an optimal set of such selections exist, which is not necessarily the one we used in this paper.

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