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Conditional Probability Based Camera Identification

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ABSTRACT

In this research, we propose a new camera identification technique based on the conditional probability features. The conditional probability features has been introduced initially for steganalysis purpose. In our work, we try to adapt those features for image forensic purpose. Specifically we focus on its performance for detection of images sources which has been taken using different iPhone cameras. By using four different iPhone cameras, we prove that the proposed technique works well based on the classification accuracy performance. This finding provides new features that may benefit image forensic works. This paper includes the introduction to conditional probability features, how the experiment works, and the discussion of the results.

INTRODUCTION

Digital images are widely available today. This is supported with the availability of wide range digital camera with different specification and functions. Despite that, the popularity of digital images also contributed by other gadget such as mobile phone which also equipped with image capturing capability.

According to Wen and Yang (2006), digital images become more frequently exhibited either directly or indirectly in court as evidence which relate suspects and the criminals. However, in current digital era, the manipulation of digital images also made simple with easily available processing tools. This is where the role of digital forensic becomes crucial. To guarantee the validity of the evidence, digital forensic helps by providing some essential information about an image. For example image forensics can be use to trace the source of a digital image. This is the case which we are looking forward in the following discussion.

CAMERA DETECTION

Much research is looking forward in identifying a unique indication that can be used to link the image to the source camera. Few methods have been proposed for that purpose. The use of statistical process control on image variations has been introduced by Bateman *et al.* (2009). In their paper, the statistical process control act as a tool to yielding anomalies in image data. This differences acts as a fingerprint to relate the image with the device.

Looking from camera operational perspective, Lukas *et al.* (2006) has shown that the camera sensor produce noise patterns that invoke a unique signature. For Bayram *et al.* (2008), the demosaicing operation in digital cameras has been used to identify the source camera model of a digital image. Choi *et al.* (2006) have proved that radial distortion (originating from the camera lens, causing straight lines to appear curved), are somewhat different for each make of camera. In addition to these methods, research against Colour Filter Array (CFA) interpolation has also been carried out by Bayram *et al* (2005), Celiktutan *et al.* (2008) and Long and Huang (2006).

In the feature extraction scheme, Kharrazi *et al.* (2004) proposed 34 specially selected image features in order to uniquely classify a camera model. Introducing the new features in our experiment, we consider this work to be at the same group as them.

CONDITIONAL PROBABILITY FEATURES

The revised probability of $\boldsymbol{B}$ when it is known that $\boldsymbol{A}$ has occurred is called the conditional probability of $\boldsymbol{B}$ given $\boldsymbol{A}$ (Bhattacharyya and Johnson, 1977) and is defined by the formula

$$P(B|A) = \frac{P(AB)}{P(A)}$$

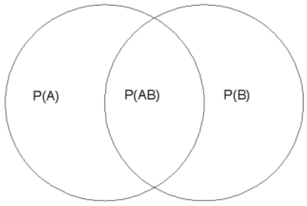

Figure 1: Venn diagram illustrates P(A), P(B), and P(AB)

Based on the concept of conditional probability, the features for our experiment are collected in horizontal, vertical and diagonal directions from JPEG coefficient values as shown in Figure 2. For each direction, ***p, q*** and ***r*** will traverse throughout the JPEG coefficient (8x8 block) in horizontal, vertical and diagonal directions, accordingly. The JPEG coefficient values consists of all the JPEG coefficients which have been quantized with the JPEG quantization table but have not been zig-zag scanned, run-length coded and Huffman coded from JPEG encoding process.

This new approach is different than the Markov process approach (Shi *et al.*, 2006), where the statistics are calculated by considering each entity in JPEG coefficient. In the Markov process approach, the features are collected by comparing all the values in the JPEG 2-D coefficient array. In this new technique, the statistics are collected in block basis and only certain values from the block were used to generate the statistics. We also exclude the DC coefficient value for each block as can be seen in Figure 2. For our experiment (Figure 2), we consider three preconditions (event ***A***)

$$A\_1:\ p < q$$
$$A\_1:\ p > q$$
$$A\_1:\ p = q$$

Next, we consider three probabilities (event ***B***)

$$B\_1:\ r < q$$
$$B\_2:\ r > q$$
$$B\_3:\ r = q$$

For three different directions, we calculate 27 statistics (9 statistics for each horizontal, vertical and diagonal direction) values in total

$$X\{i, j\} = \hat{p}\,(B_i \mid A_j)\,,$$
$$j = 1, 2, 3,4,5,6 \text{ and}$$
$$i = \{1,2,3$$

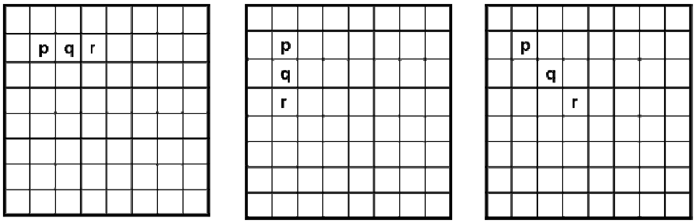

Figure 2: Conditional probability directions: horizontal, vertical and diagonal

EXPERIMENTAL SETUP

To evaluate the performance of the proposed camera identification technique, we captured images with four different cameras for iPhone. At the time of writing, Flickr (the popular image and video hosting site) states that this device is the current most frequently used camera model by its users. The iPhone is not primarily engineered for photography, and as such uses inexpensive camera components. The image resolution is 2 Megapixels (1600x1200), and there exists no optical or digital zoom. There are also no settings that can be changed, meaning the error correction and image enhancement processes are automatic (if they even exist at all).

Test Environment

It is very important that the environment in which the images are captured is controlled as much as possible to ensure that it has a restricted impact on the image acquisition process. Without controlling the environment, it might be possible that each device produces different results, not because of the camera make-up, but because of an external factor such as temperature changes, or changes in ambient lighting due to sunlight or cloud cover. In order to nullify the external influences, we took the images from inside a room that had no windows, meaning that the ambient lighting is more controlled. The scene is lit via fluorescent lighting, which is well known for flickering. Whilst this is not ideal for most experiments, it is quite useful for testing how effectively each device reacts to the light flicker. The room was also air conditioned to a constant temperature to reduce the potential impact of temperature changes affecting the results.

Test Scenes

The scene itself comprises a white bowl containing colourful confectioneries that force the images to inherit a wide variation of colour shifts. Whilst colour shifts of this degree are rarely seen in real world scenes, it acts as a good method for testing the colour interpretation for each camera. Surrounding the bowl, are 10 angle reference points which are used to align each device to the same position (Figure 3). When introducing angles, we simultaneously introduce natural shadowing from the object matter, meaning we can later review whether or not the discrepancies are connected to lighting, if need be. However, what we are mainly reviewing is the image data obtained per device, on a per angle basis. Comparisons are made across all iPhone data solely to confirm that each model inherits the same characteristics. Ten images are captured from each of these ten angles, meaning 100 images are taken for each device. A bendable tripod is used to ensure that the images taken from all devices are as similar as possible.

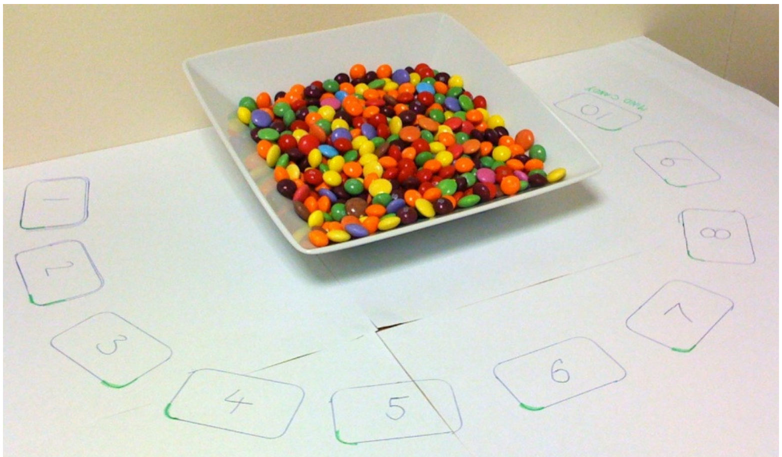

Figure 3: Test scenes

With all the images ready, the proposed technique is conducted to produce the features for the subsequent classification process. The freely available LibSVM (Chang and Lin, 2001) was then used as the classifier. For SVM, the *soft margin* and *gamma* parameters are determined using parameter selection tool, 'grid.py' that was available from the LibSVM package.

RESULT AND DISCUSSION

Using the same performance heuristic in Wahab et al. (2009), classification accuracy was used to measure the performance of the proposed technique. When two IPhone used, the proposed features has shown a very good performance when it can perfectly classify image's based on their source (Table 1). By increasing the number of IPhone in the experiment, the performance can be seen decrease (Table 2 and Table 3). This is expected due to the additional number of features which may contribute to overfitting problem.

TABLE 1: The confusion matrix for two camera identification case

	IPhone 1	**IPhone 2**
IPhone 1	100%	0%
IPhone 2	0%	100%

TABLE 2: The confusion matrix for three camera identification case

	IPhone 1	**IPhone 2**	**IPhone 3**
IPhone 1	89.5%	0%	10.5%
IPhone 2	0%	100%	0%
IPhone 3	0%	0%	100%

TABLE 3: The confusion matrix for four camera identification case

	IPhone 1	**IPhone 2**	**IPhone 3**	**Iphone 4**
IPhone 1	84.2%	0%	5.3%	10.5%
IPhone 2	0%	100%	0%	0%
IPhone 3	0%	0%	94.7%	5.3%
IPhone 4	10.5%	0%	5.3%	84.2%

Comparison with another steganalysis features

Conditional probability features has been proposed for steganalysis purpose. For comparison purpose, the experiment was repeated with another features previously proposed for the same objective. The features are as below:

- 23 DCT Features by Fridrich (2004)
- 127 Features by Pevny and Fridrich
- 324 Markov Model features by Shi *et al.* (2006)
- 81 Calibrated Markov used by Pevny and Fridrich (2007)

The result in Table 4 shows how our proposed features outperform the other features.

TABLE 4: The classification accuracy for camera identification with un-touch images

	Fridrich	**Pevny & Fridrich**	**Calibrated Markov**	**Markov Model**	**Conditional Probability**
2 iPhones	85	92	71	98	98
3 iPhones	78.67	75.33	48	94.67	96.7
4 iPhones	70.5	66.5	44	91.5	92.5

We are looking forward at the performance of the proposed features with the processed images. For that purpose, we cropped the image into half of its original size (800x600) and compressed with quality factor of 80 using Matlab 8.0 software. The result is shown in Table 5.

TABLE 5**:** The classification accuracy for camera identification with cropped and compressed images

	Fridrich	**Pevny & Fridrich**	**Calibrated Markov**	**Markov Model**	**Conditional Probability**
2 iPhones	88.0	90.0	68.67	97.3	98.6
3 iPhones	79.1	74.0	53.56	94.4	97.8
4 iPhones	69.8	67.8	50.0	90.0	92.5

There is still another advantage, where our proposed method only used 27 feature vectors compared to the other features. This could help to reduce the time needed for training and testing, especially when real world implementation put into consideration.

CONCLUSION

By using four different iPhone cameras, we prove that the proposed features perform well based on the classification accuracy performance. Even though the performance was slightly decreased with additional number of camera, it is possible to improve the result by providing larger image data set which may cover a large range of texture and scenery for each camera.

REFERENCES

Bateman, P., Ho, A.T.S. and Woodward, A. 2009. Image Forensics of Digital Cameras by Analysing Image Variations using Statistical Process Control. *IEEE International Conference on Information, Communications and Signal Processing (ICICS'09)*, Macau, China.

Bayram, S., Sencar , H.T., Memon, N. and Avcibas, I. 2005. Source camera identification based on CFA interpolation. *IEEE International Conference on Image Processing, 2005. ICIP 2005*, **3**: 69-72.

Bayram, S., Sencar, H.T. and Memon, N. 2008. Classification of digital camera-models based on demosaicing artifacts. *Digital Investigation: The International Journal of Digital Forensics & Incident Response*, **5**: 49-59.

Bhattacharyya, G.K. and Johnson, R.A. 1977. *Statistical Concepts and Methods*. Wiley.

Caliktutan. O., Sankur, B. and Avcibas, I. 2008. Blind Identification of Source Cell-Phone Model. *IEEE Transactions on Information Forensics and Security*, **3**(3): 553-566.

Chang, C.C. and Lin, C.J. 2001. LIBSVM: a library for support vector machines. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm.

Fridrich, J. 2004. Feature-Based Steganalysis for JPEG Images and Its Implications for Future Design of Steganographic Schemes. *Information Hiding*: 67-81.

Kharrazi, M., Sencar, H.T. and Memon, N. 2004. Blind Source Camera Identification. *IEEE International Conference on Image Processing, ICIP*: 709-712.

Long, Y. and Huang, Y. 2006. Image Based Source Camera Identification using Demosaicking. *8th IEEE Workshop on Multimedia Signal Processing:* 419-424.

Lukas, J., Fridrich, J. and Goljan, M. 2006. Digital Camera Identification from Sensor Pattern Noise. *IEEE Transactions on Information Security and Forensics*, **1**(2): 205-214.

Pevny, T. and Fridrich, J. Merging Markov and DCT features for multi-class JPEG steganalysis. *Proceedings of SPIE, Electronic Imaging, Security, Steganography, and Watermarking of Multimedia Contents IX*, San Jose, CA.

San, C.K., Edmund, L., and Kenneth, W. 2006. Source Camera Identification using Footprints from Lens Aberration. *Proceedings of the SPIE*, **6069**: 172-179.

Shi, Y.Q, Chen, C. and Chen, W. 2006. A Markov Process based Approach to Effective Attacking JPEG Steganography. *Information Hiding:*249-264.

Wen, C.Y. and Yang K.T. 2006. Image authentication for digital image evidence. *Forensic Science Journal,* **5** : 1-11.