# A TWO DIMENSIONAL CAMERA IDENTIFICATION METHOD BASED ON IMAGE SENSOR NOISE

*Lit-Hung Chan, Ngai-Fong Law and Wan-Chi Siu*

Centre for Signal Processing
Department of Electronic and Information Engineering
The Hong Kong Polytechnic University

## ABSTRACT

In this paper, we propose a two-dimensional digital camera identification method based on the photo-response non-uniformity (PRNU). The traditional identification method is based on a correlation estimator which calculates the correlation between the reference PRNU and the PRNU extracted from the testing image. However, the correlation calculated greatly depends on the image content. To reduce the image content effect in classification, a correlation predictor is trained based on different types of image features. By using the predicted correlation and the actual correlation, a 2D classifier using support vector machine is proposed in this paper. Experimental results show that the proposed method can have a more flexible threshold setting which gives a better identification results as compared to the traditional identification method.

***Index Terms*—**Digital Forensics, Camera identification, Photo-response non-uniformity (PRNU)

## 1. INTRODUCTION

Digital camera identification by using the photo-response non-uniformity (PRNU) was first introduced by Lukas et al. [1]. A denoising filter [2] is used to extract the PRNU as the difference between the original image and the denoised image. This noise residue contains significant characteristics of the PRNU and hence achieves a good performance in camera identification. To reduce the random noise and obtain a reliable estimate, the PRNU of a particular camera is obtained by averaging the noise residues extracted from a set of images taken by that camera. Then, the correlation between the PRNU from an image and that of a camera is compared to see whether the image is taken from that particular camera.

Later, it was found that the correlation can easily be affected by the image content. Chen et al. proposed a shaping factor to attenuate PRNU features in the identification model [3]. To achieve the optimal detection, a correlation predictor was proposed to assign different weightings to different image regions [4]. In this way, a large weighting is applied to region producing a reliable estimate. Using the correlation predictor, a weighted correlation is obtained for camera identification.

Indeed, the predicted correlation can classify images according to their features. In this paper, we consider the predicted correlation as another feature to be used in support vector machine. We propose a 2D classifier so that a flexible correlation threshold can be used for camera identification.

The rest of the paper is organized as follows. We will first describe the correlation detector of the traditional camera identification in Section 2. Section 3 then introduces the correlation predictor. Our proposed 2D classifier will be discussed in Section 4. Experimental results will be given in Section 5. Finally, Section 6 concludes the paper.

## 2. TRADITIONAL CAMERA IDENTIFICATION BASED ON PRNU FEATURE

PRNU shows the pixel to pixel difference under illumination of light. It is caused by the inhomogeneity of silicon wafers and manufacturing imperfection [5]. These kinds of imperfections make images taken from a particular camera having the same kind of pattern noise which acts like a fingerprint of the camera. To obtain PRNU feature, the original image is first subtracted from its denoised version to give the noise residue. Let $W$ be the noise residue. It can be written as,

$$W = IK' + \varepsilon, \tag{1}$$

where I is the intensity of the image, $K'$ is the PRNU multiplicative feature and $\varepsilon$ is the noises term. This noise residue $W$ contains significant part of the PRNU feature. It can be used in estimating the reference PRNU of a particular camera and feature comparison. The reference PRNU $\widehat{K_c}$ from $N$ images taken from the same camera can be calculated through a maximum likelihood approach as,

$$\widehat{K_c} = \frac{\sum_{k=1}^{N} W_k I_k}{\sum_{k=1}^{N} (I_k)^2} \tag{2}$$

where $W_k$ and $I_k$ are the noise residue and intensity of $k$th image.

For feature comparison, normalized cross-correlation can be used. Let $W_p$ and $I_p$ be respectively the noise residue containing the PRNU feature and the intensity of a testing image. The normalized cross-correlation that measures the similarity between the reference PRNU and the testing PRNU is defined as,

$$\rho_C(p) = corr\left(W_p, I_p\widehat{K}_c\right) = \frac{(W_p-\overline{W_p})\left(I_p\widehat{K}_c-\overline{I_p\widehat{K}_c}\right)}{\|W_p-\overline{W_p}\|\left\|I_p\widehat{K}_{c_c}-\overline{I_p\widehat{K}_c}\right\|}, \quad (3)$$

where the bar above the symbol denotes its mean value. A high cross-correlation implies a high chance that the testing image us taken by the same camera as the reference PRNU. This correlation shows the similarity between features. The higher the value indicates the testing image is more likely taken by the same camera as the reference PRNU.

The traditional classification approach uses a binary hypothesis test for decision making. Let H0 be the hypothesis that the testing image and the reference PRNU are from different cameras while H1 be the hypothesis that they are from same camera. First, the reference PRNU for a particular camera is generated using eq (2). Second, images from that camera are used to generate the probability density function for the hypothesis H1 and images from other cameras are used to generate the probability density function for the hypothesis H0. Then the false acceptance rate (FAR) is set for the false tolerance of the system. At a given FAR, a threshold is set to minimize the false rejection rate (FRR) which is used for performance evaluation.

## 3. CORRELATION PREDICTOR

The correlation in eq (3) can easily be affected by the image content such as image intensity, texture and signal flatting. To achieve an optimal identification, a correlation predictor was proposed to assign different weightings to different image regions accounting for different shaping factors for the PRNU [3,4]. An image is first divided into a number of non-overlapping blocks. For each block, three types of features (intensity, texture, and signal flatting) are extracted. Besides, the correlation between the PRNU feature in each block and the reference PRNU is calculated. Then a linear prediction model is built to take into account the effect of the image feature to the correlation, i.e.,

$$\rho = H\theta, \quad (4)$$

where $\rho$ is the column vector consisting of correlation terms and $H$ is a matrix whose column and row contain respectively the image features and the number of image data. By using least square estimator, the coefficients term $\theta$ for each feature can be solved. With the trained coefficients, the predicted correlation can by calculated by eq (4) with using the same type image features.

This predicted correlation helps to assign different weightings to the correlation for each block. In particular, a large weighting will be given to block with a large predicted correlation. With a large predicted value, the attenuation factor of the PRNU feature is low which implies that the correlation of that block is reliable. Similarly, a small weighting is assigned to block with a low predicted value. In fact, this mechanism achieves a generalized matched filter [4]. The weighted correlation is the sum of the normalized weighted non-overlapping block correlation for the image.

## 4. PROPOSED CLASSIFICATION METHOD USING PREDICTED VALUE

The predicted correlation is used to decide the weights to the correlation in different blocks [3]. Indeed, it can be used to classify images according to their features. In this paper, we would like to extend its usage in the classification procedure. We consider the predicted correlation as another feature used together with the actual correlation to give a two-dimensional classification.

For each image, the noise residue is first extracted by using the BM3D instead of the wavelet based filter [2]. It is because the BM3D shows a better identification result in [6] which also in line with our experimental results. The noise residue is then divided into M non-overlapping blocks. For each block, the correlation is calculated by eq (3). Let the correlation for each block be $\rho(b)$ where $b$ =1,2,…M. Then the actual correlation for each image is obtained as,

$$\rho = \sum_{I\in M} \frac{\rho(b)}{M}. \quad (5)$$

The prediction coefficients $\theta$ in eq (4) are trained for a particular camera. The correlation predictor can then be used to estimate the correlation based on the image content. Let the predicted correlation for each block be $\hat{\rho}(b)$ where $b$ =1,2,…M. Then the predicted correlation for each image can be obtained as,

$$\hat{\rho} = \sum_{I\in M} \frac{\hat{\rho}(b)}{M}. \quad (6)$$

Fig.1 shows a plot of the actual correlation against the predicted correlation for two set of images. The block size used to train the predictor was 128x128 and the image size used for testing was 512x512. The first set of the images consisted of 400 images (represent by blue cross) taken from the same camera (Minolta DiMAGE X) that generated the reference PRNU. The other set of images (represent by green dot) consisted of 400 photos taken by each of following cameras: Digital Cannon IXUS 65 and Sony DSC T-500. Fig.1 shows an important feature of the predictor: the predicted value is close to the actual value if that image comes from the same camera as the reference PRNU. Otherwise, the predicted value is independent of the actual correlation. This suggests that the strategy used to classify images from the same camera and different cameras should vary with the predicted value.

If using solely the actual correlation, we can only have a single value for threshold decision. However, we can see from Fig.1 that the distance between the blue cross and the green dot increases with the predicted value. Therefore the threshold decision should also vary with the predicted value. To have different thresholds for different predicted values, we propose to use both the predicted correlation and the actual correlation for classification. The support vector machine (SVM) is used. It was implemented with Matlab default statistical learning toolbox. The kernel function used was the radial basis function and the decision boundary was solved by quadratic programming optimization. Other parameters for the SVM were set to be default.

To show the advantage in using proposed 2D classifier as compared to the traditional classifier, the 2D classifier was trained from half of the data in Fig.1. To give a more reasonable range for the training threshold, some artificial data was generated in SVM training to give an upper bound and lower bound for the threshold. The artificial data at upper bound was set to have the actual correlation equals to the maximum of the actual correlation from different camera times 1.5 while that at lower bound was set to have the actual correlation equals to the minimum of the actual correlation from the same camera divided by 1.5 in the training set. Fig.2 shows the training results.

After training, we used the second half of the data in Fig.1 to test the trained classifier. Both the traditional and the 2D classifiers were set to have the same false rejection rate (FRR). Fig.3 shows a plot of the threshold values of the traditional and the 2D classifiers. For the traditional classifier, the same threshold value is used irrespective of the predicted correlation. We can see that some data were falsely accepted by the traditional classifier. In contrast, our 2D classifier adopts different threshold values according to the predicted correlation and the actual correlation. Those falsely accepted data were correctly identified by our proposed classifier. This shows the advantage of our proposed algorithm which can identify images not solely based on the actual correlation but also based on the prior knowledge of the image content. Fig.3 considered the FAR by fixing the FRR. In fact, similar improvement on FRR can be found by fixing the FAR.

## 5. EXPERIMENTAL RESULTS

We adopted the same experimental settings as that described in Section 4. To simplify computations, the color image was first converted to gray color image instead of calculating the PRNU in different color channels. There were three cameras used in the experiment, including Minolta DiMAGE X, Digital Cannon IXUS 65 and Sony DSC T-500. For each camera, 50 images were used to generate the reference PRNU for that camera using the maximum likelihood approach described in section 2. Afterwards, 50 images apart from those used to create the reference PRNU were used to train the correlation predictor by using the method described in section 3. Other 400 images for each camera were then used for performance evaluation.

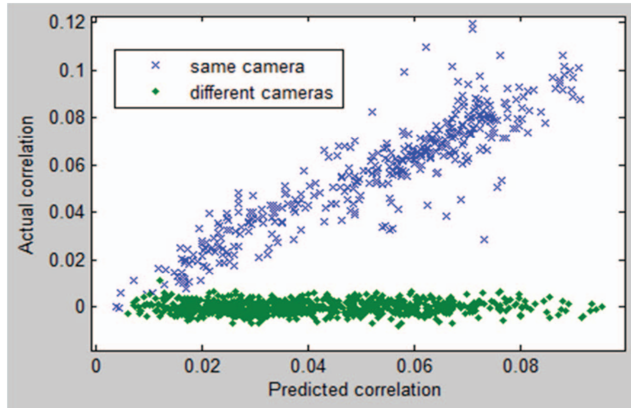


Figure 1. Plot of $\rho$ vs $\hat{\rho}$ for 400 images from Minolta DiMAGE Xt(blue cross) and 800 images from other cameras(green dot) using predictor trained from another 50 images from Minolta DiMAGE Xt

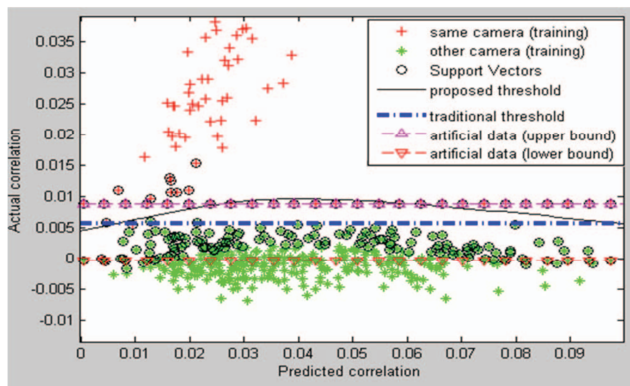


Figure 2. A close up of the proposed threshold and traditional threshold using half of the data in Fig.1 for training

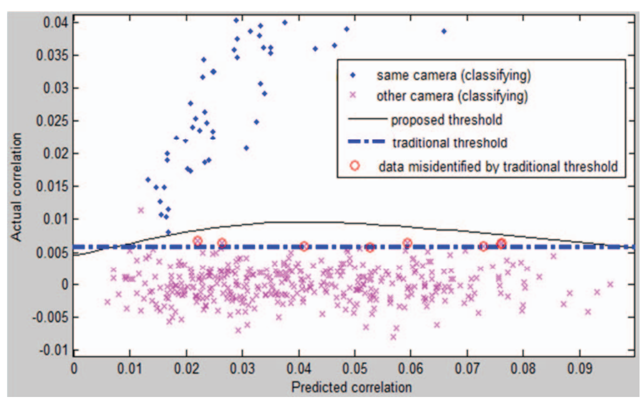


Figure 3. Classfying result using training threshold in Fig.2

The classification problem here is a binary hypothesis problem. Let H0 represents the hypothesis that the testing image and the reference PRNU are from different cameras while H1 represents the hypothesis that they are from the same camera. For each camera, there were 800 images for hypothesis H0 and 400 for hypothesis H1. For images in hypothesis H1, they consisted of 400 images from each of the other camera in the experiment. To train the 2D classifier, half of the data from hypothesis H0 and hypothesis H1 were randomly picked for training. Some artificial data were generated as mentioned in Section 4 to give the upper and lower bound for the training threshold. Afterwards, the other half of the data from hypothesis H0 and hypothesis H1 were used for classification. As the result of SVM classifier varies with different training set and classifying set, we repeated the SVM training and classifying processes 50 times with the same pool of data but with random combination in training set and classifying set in order to achieve a reliable result.

We compared the performance of our proposed 2D classifier with the traditional classifier using either actual correlation [1] or weighted correlation [3] to make decision. We used the FAR in the 2D classifier to set the threshold in the traditional classifier in the same training set and then compared the FAR, FRR and accuracy in the classifying set.

Table 1 shows the average performance of our proposed method and the traditional methods over 50 trials for different training and classifying sets. In terms of accuracy and FRR, our proposed method shows improvement in camera 2 but has comparable performance in camera 1 and camera 3. The reason is that, under the case of high accuracy, the overlapping area for null hypothesis and alternative hypothesis data is low. Hence, the performance of using the same threshold and the varying threshold values would be similar. For the case of low accuracy as in camera 2, the advantage of using flexible threshold of the 2D classifier is obvious.

One interesting observation is that, although we set the same FAR in the training set, the FAR of the proposed method had a lower value than the traditional methods [1,3] in the classifying set. This shows our method is having a better preservation in terms of FAR. The reason is that, the overlapping area of the null hypothesis and alternative hypothesis data is concentrated at the small predicted correlation. The proposed threshold can help to prevent the data being falsely accepted in large predicted correlation value.

## 6. CONCLUSION

In this paper, we developed a new approach to use the correlation predictor in source camera identification. In particular, a two-dimensional classifier using both the predicted correlation and the actual correlation is proposed so that the decision threshold can be set flexibly. We compared our proposed method with the traditional methods of using either actual correlation or weighted correlation. Experimental results show that our proposed method is able to improve the performance, especially for the low accuracy case.

In fact, the predicted correlation can be used to determine whether the types of images are suitable for camera identification using PRNU feature. If not, other identification methods should be used. Our future works is to explore the use of a combined identification method.

TABLE 1. AVERAGE PERFORMANCE IN TERM OF FAR, FRR AND ACCURACY COMPARING PROPOSED METHOD AND TRADITIONAL METHODS

| | | Camera 1 | Camera2 | Camera3 |
|---|---|---|---|---|
| FAR (%) | Method[1] | 0.25 | 0.23 | 0.26 |
| | Method[3] | 0.23 | 0.28 | 0.28 |
| | Proposed Method | 0.13 | 0.11 | 0 |
| FRR (%) | Method[1] | 1.32 | 7.08 | 1.11 |
| | Method[3] | 1.31 | 5.65 | 1.51 |
| | Proposed Method | 1.42 | 4.79 | 1.24 |
| Accuracy (%) | Method[1] | 98.43 | 92.69 | 98.63 |
| | Method[3] | 98.46 | 94.07 | 98.21 |
| | Proposed Method | 98.45 | 95.10 | 98.76 |


## ACKNOWLEDGMENT

Chan Lit Hung acknowledges the research studentships provided by the University.


## 7. REFERENCES


[1] J.Lukas and J.Fridrich, “Digital camera identification from sensor pattern noise,” *IEEE Trans. Information Forensics and Security*, vol.1, no. 2, pp.205-214, 2006.

[2] M. K. Mihcak, I. Kozintsev, and K. Ramchandran, “Spatially adaptive statistical modeling of wavelet image coefficients and its application to denoising,” in *International Conference on Acoustics, Speech, and Signal Processing*, vol. 6, pp. 3253–3256, 1999.

[3] M. Chen, J. Fridrich, and M. Goljan, “Digital Imaging Sensor Identification (Further Study),” *in Proc. SPIE, Electronic Imaging, Security, Steganography, and Watermarking of Multimedia Contests IX,* San Jose, CA, Jan. 28-Feb.2,2007, vol.6505, pp. 0P-0Q

[4] S. M. Kay, *Fundamentals of Statistical Signal Processing*, vol. II Prentice-Hall, New York, 1998,

[5] J. R. Janesick, *Scientific Charge-Coupled Devices*, Bellingham, WA: SPIE, vol. PM83, 2001.

[6] G.Chierchia, S.Parrilli, G.Poggi, C.Sansone and L.Verdoliva, “On the influence of denoising in PRNU based forgery detection,” *Proc. of the 2nd ACM workshop on Multimedia in forensics, security and intelligence,* Italy, 2010.