Improved Image Source Analysis

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Abstract. In this paper, we present an improvement over the digital camera identification technique based on sensor noise proposed by Lukas *et al.*[1].
The project is a joint work with the C.N.C.P.O. (Centro Nazionale per il Contrasto della Pedopornografia sulla rete internet, Dipartimento della Pubblica Sicurezza del Ministero dell'Interno, by the Italian Servizio Polizia Postale e delle Comunicazioni).
Our main goal is to develop a a full fledged system prototype (a tool set supported by a robust methodology) able to give an answer to the following question: *which camera among a predefined set could be the source of a given digital image ?* This was formerly known as the problem of the identification of how a given image has been generated). As this method as been conceived as a digital image forensics technique to support policy investigation, the result is acceptable only if it comes with the highest degree of accuracy.
The project started from the results presented in [1] which use the characteristic noise of the sensor, typically a CCD (charge-coupled device), as a fingerprint to identify the source camera. We first implemented a framework to perform an experimental analysis of such a technique and to verify on the field if it could be successfully used for our specific purposes with the necessary reliability. During this phase we stressed the original technique with a big amount of consumer and professional digital cameras populating our data base with several thousand of digital images. All the test confirmed that the pixel non-uniformity noise could be successfully used to identify the image source but for some specific camera models we got a sort of pattern clash and many images produced low correlation values with more than one reference pattern previously extracted from the cameras under investigation including the true source. In these cases the values were also too close to the rejection threshold. This has been considered an important issue to adopt the Fridrich's approach for digital image forensics.
Moreover the process to define the acceptance threshold based on the Neyman-Pearson approach, which has been originally employed to define the acceptance threshold t minimizing the false reject rate (FRR), resulted too time consuming e not enough flexible because the necessary accuracy can be reached only if the system can learn from the analysis of a considerable number of images from a known source and when the camera set or the input image set change all the threshold t must be recomputed.
In this paper we present three variants to the original technique based on a different approach in the classification phase to identify the source camera. We first define a set S of candidate digital cameras, than we extract the sensor noise reference pattern for each camera. Then we take a small set (even a dozen) of randomly chosen pictures for each camera. For each image we calculate the correlation factor against the reference

pattern of each camera. Finally we use these values as training set for a SVM classifier (Support Vector Machine) with a number of input attributes equal to the cardinality of the set S. Similarly we defined a test set to verify the result of the training. The trained classifier is now ready to answer to the question *which camera among the set S produced the image I ?* In fact we recalculate the correlation with all the reference patterns and we give the resulting values as input to the SVM which can provide us with the source camera identification.
We have extensively tested the approach we propose and, as shown in the section 3, it led us to a double improvement:
1. on one hand our approach improved the accuracy of the final result especially in the case of cameras with sensor noise patterns which produces low correlation values or simply too close to be considered distinct. In facts, the SVM can identify the source discriminating these values considering the correlation values produced by the patterns of the other cameras of the set S instead of comparing each correlation value against a single predefined threshold value.
2. on the other hand our approach produced a considerable speed up of the whole process for source camera identification, reducing the amount of the images necessary to train the system establishing the threshold of acceptance. This becomes even more meaningful if is considered that during the investigation often we had to work with a set of hundred candidate cameras, and many of these belong to the same producer / model.

1 Introduction

2 System Components

Comparing our system with the original one proposed by Lukas *et al.* [1] three main differences arise:

1. The process to extract the camera reference pattern is based on a series of images with a very smooth subject, such as a white and uniformly lighted wall. Moreover the process for pattern extraction has been logically separated by the process for source camera identification. More in details, for each camera k we produce a set of N^k template images T, and for each image $I_x, x = 1, \ldots, N^k$ we apply a filter F to remove the scene content leaving only high frequency noise. The final camera reference pattern np^k is obtained by averaging the residual noise pattern as shown in 1

$$np^k = AVG_x(n_x = I_x - F(I_x)) \tag{1}$$

2. The denoising filter F is based on our implementation of a flexible wavelet package able to efficiently manage images of any size (using padding to a smallest power of 2) (with 8 or 16 coefficients). In this way ...

3. The identification process is based on a trained SVM. The target input image I^T is filtered with the same filter F to obtain the image noise pattern np^{I^T}. Then, for each camera k we calculate a correlation value between the image noise pattern np^{I^T} and the camera noise pattern np^k:

$$\rho^k = corr(np^{I^T}, np^k), k = 1, \ldots, N \tag{2}$$

the resulting ordered data set (just one raw) becomes the SVM input, that will give the final answer providing the user with the index k of the camera whose reference pattern is closest to the image pattern. Obviously this answer will consider the global distance, considering also the relations of the chosen reference pattern with all the other cameras reference pattern.

We will demonstrate how item 1 produces better reference patterns, comparing the correlation values between generic input images and our reference pattern with the ones obtained using reference pattern extracted from generic images.

Item 2 radically reduced the use of cropping or resizing operator, giving again higher correlation values. Moreover this makes the system suitable to efficiently handle real word images.

We will demonstrate how item 3 improved the performance of the overall process reducing the classification errors.

3 Experimental Analysis

Camera model	# identification error Fridrich's method	# identification error SVM classifier
Canon 400D	2	0
Canon $A400_1$	8	2
Canon $A400_2$	1	0
HP E327	5	0
Kodak CX7530	1	0

4 Conclusion

References

1. Lukas, J., Fridrich, J., and Goljan, M. Digital camera identification from sensor pattern noise. *Information Forensics and Security, IEEE Transactions on 1*, 2 (June 2006), 205–214.