A Review of “Camera Attribution Forensic Analyzer in the Encrypted Domain”

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***Abstract*—This paper is a review of a work previously published by the authors at IEEE WIFS’18 (Workshop on Information Forensics and Security), which received the Best Paper Award, and contains a summary of its main results. In WIFS’18 we proposed a new framework for the secure outsourcing of the image source attribution problem, in which the Photoresponse Non-Uniformity (PRNU) is used as a fingerprint to decide whether a test image was taken with a specific camera device. This method is fully unattended, that is, the secret key owner does not take part during the process. To this aim, we introduced improvements on the state-of-the-art in secure and unattended solutions for denoising. We also showed how to homomorphically perform filtering, polynomial, denoising and pixel-wise operations in a single round without the need of an interactive protocol.**

***Index Terms*—Photoresponse Non-Uniformity; lattice-based cryptosystems; digital media forensics; camera attribution forensic analyzer**

Type of contribution: *Already published research*

I. Introduction

In this paper we present the results of our research that was previously published at the Workshop on Information Forensics and Security (WIFS) in 2018 [1].

A. Motivation

All digital imaging sensors intrinsically present a noise pattern called PRNU, which is due to tiny and random imperfections on the silicon wafer. PRNU is becoming particularly relevant within digital media forensics, as it can be used as a fingerprint to determine whether a given image was taken by a certain device. Consequently, many works have made use of its uniqueness feature for a wide range of applications; which includes identification and clustering of acquisition devices.

However, an important problem that these applications share is that they are computationally intensive and work with very large databases. Actually, although buying computing power and database storage as needed appears as an interesting solution, the privacy-sensitive nature of forensic data prevents from directly outsourcing it unencrypted.

Recent results from [2], [3] show that the estimated PRNU fingerprints leak a considerable amount of information of the images used for extraction. This constitutes a serious privacy threat and suggests that for some scenarios (e.g., child pornography crimes), camera fingerprints should be protected not only when outsourcing, but at all times during investigations.

B. Main results of [1]

The secure scheme proposed in [1] was exemplified for the case of PRNU extraction/detection, but it covers many other forensic tools.

The main technical results are the following:

- An efficient Wavelet-based denoising primitive is introduced. The main novelty relies on the use of a new homomorphic threshold function by means of the “lowest digit removal” polynomials introduced in [4], [5].
- Further optimizations on the Wavelet denoising primitive are presented, consisting of the use of efficient NTT (Number Theoretic Transforms) packing.
- The previous encrypted denoising primitive is used as a building block in a more complex use case as the PRNU extraction/detection for camera attribution. The proposed method is able to compute the process for extraction/detection in an unattended way, that is, without additional interactions between the client and server.

II. Proposed Scheme

A. Related Works

To the best of our knowledge [6], there are two different approaches for secure camera attribution: (a) Mohanty *et al.*, [7], [8] who combine a trusted environment (ARM TrustZone) for the computation of the PRNU fingerprint, with the Boneh-Goh-Nissim (BGN) cryptosystem for the matching, and (b) ours [1], which proposes a more flexible solution that can be implemented on a general purpose architecture and does not require access to a trusted environment.

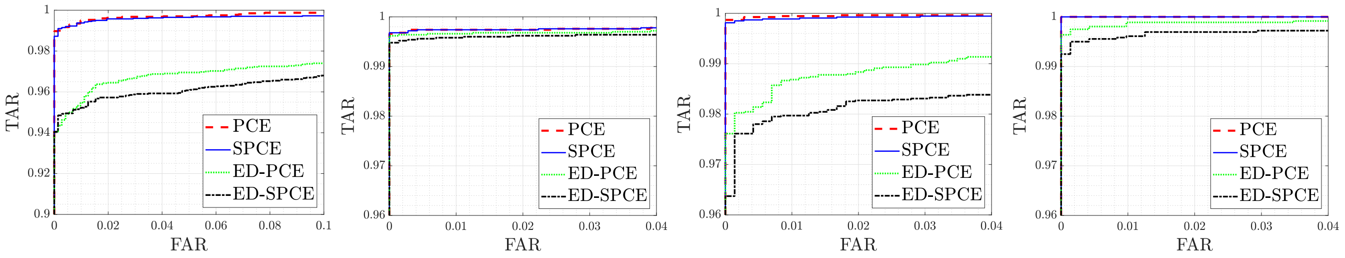
As we discussed in [6], although Mohanty *et al.*’s scheme evaluates most of the computation in the clear, their runtimes do not improve those obtained by our solution. In fact, the PRNU matching in their scheme could be more efficiently calculated by substituting the BGN cryptosystem with more modern lattice-based cryptosystems. In relation to this, it is worth mentioning that, if available, our solution could also use a trusted environment to improve the efficiency.

B. Unattended and Secure Camera Attribution

Our proposed scheme is based on the use of an RLWE (Ring Learning with Errors) cryptosystem equipped with an adequate use of NTT transforms and efficient signal pre-/post-coding operations before/after encryption/decryption.

Due to space restrictions, we refer the reader to [1] for more details. A full diagram of the proposed framework is included in [1, Fig. 1].

The main challenge is the efficient evaluation of the threshold function used in the Wavelet denoising primitive. By approximating this threshold with a quantization operation, we can leverage the “lowest digit removal” polynomials as a mechanism to homomorphically evaluate thresholding. The



(a) Nikon D7000. (b) Nikon D90. (c) Canon 1100D. (d) Nikon D3000.

Fig. 1: True Acceptance Rate (TAR) vs. False Alarm Rate (FAR) for 4 different camera devices. PCE represents the result obtained with the denoising in [9] and the PCE statistic [10], SPCE is the simplified detector in [1, eq. (4)] applying the denoising from [9], ED-PCE is the PCE statistic using the encrypted denoising described in [1, Sec. 3.2], and ED-SPCE stands for the simplified detector discussed in [1, Sec. 3].

use of this functionality results in a considerably reduction of the ciphertext size and the depth of circuit to be computed.

III. Performance Evaluation

We evaluated in [1] our secure framework in terms of efficiency, security and performance. To this aim, we securely performed the PRNU detection test, in which the PRNU estimate is tested against the test image via the statistical distribution of a score on both hypothesis (i.e., the image contains or not the PRNU estimate); whereas the PRNU estimate was obtained in the clear domain.

This scenario corresponds to the case where the police have confiscated the camera of a suspect, and would like to check whether an image has been taken by this camera.

Due to legal restrictions, this test image cannot be outsourced without being previously protected. On the contrary, as we have control of the camera, we can take flatfield images to perform the extraction without any privacy leakage.

A. Implementation and execution times

We implemented our scheme taking advantage of the RNS variant of the FV cryptosystem [1], and execution times were measured on an Intel Xeon E5-2667V3 at 3.2GHz using one core for the non-parallelized choice.

Table I reports the runtimes for encrypted detection assuming that the PRNU estimate and the test image are aligned.

TABLE I: Runtimes for Encrypted PRNU detection (2048 × 2048 image)

Parallelization (cores)	1	8	16	20
Encrypted Detection (min)	128.33	16.05	8.03	6.53
Encryption + Pre-coding (s)	3.6 (1 core, client-side)			
Decryption + Post-coding (ms)	27 (1 core, client-side)			

The introduced improvements on the unattended denoising primitive result to be fundamental in achieving the above execution runtimes.

B. PRNU Detection Performance

We utilized a database composed of 2639 TIFF images taken from 16 digital camera devices. The fingerprint was extracted for each different camera device from 50 randomly chosen TIFF images. For the detection phase, we considered crops of the JPEG-compressed version of the TIFF images with size 1536 × 1536 and a quality factor of 95.

Figure 1 compares the performance of the detector in [1, Eq. (2)] (dot product) with the Peak to Correlation Energy (PCE) detector [10], both when the popularly used image denoising in [9] and when our encrypted denoising are used to obtain the residues of the different test images. As the fingerprint estimate is obtained in the clear, we used in all the experiments the denoising method from [9] for extraction.

IV. Conclusions and Future Work

This work reviews the results obtained in a previously published paper [1] by the authors. In [1], we introduced an unattended secure framework for outsourcing computation which could perform the PRNU extraction/detection phases without any additional interaction with the client. We evaluated the performance of our method in a concrete scenario on which the test images have to be protected.

Our results show the feasibility of source camera attribution in the encrypted domain. Even so, there is still room for improvement, and we are currently working on a complete evaluation of the encrypted extraction. This includes further refinements on the encrypted denoising primitive, and a reevaluation of the use of the underlying RLWE cryptosystem profiting from the most recent results in the field.

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