Retrieval of Large Scale Images and Camera Identification via Random Projections

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Abstract- *Retrieving of large size images from a huge collection is a relevant and a difficult task. And matching those images with the source camera is tedious and time consuming. There are Sensor imperfections in the form of Photo Response Non Uniformity (PRNU) patterns is a well-established fingerprinting technique to link pictures to the camera sensors that acquired them and can be used for this purpose, but due to noise like characteristics present in them and large size of PRNU makes it difficult to compress the objects and increases the complexity of the matching operational tasks. Thus an efficient technique is been proposed called as Random Projections for the retrieval of images on a large scale which not only compress the images but also match them according to the source camera through which they have acquired. Circulant matrices are used in this technique to address the complexity of implementing Random Projections.*

KeyWords: Sensor imperfections, Photo Response Non Uniformity, Camera sensors, Random Projections, Circulant matrices.

1. INTRODUCTION

Every day, millions of pictures are uploaded, shared, and browsed by Internet users, which results in very large collections of images that require an efficient solutions for their management [1].**I**maging sensor imperfections can be considered as a unique camera fingerprint identifying a specific acquisition device, which enables various important forensic tasks, such as camera identification, camera linking, recovery of processing history, detection of digital forgeries. In this sense, a technology called content-based image retrieval has received a lot of attention in recent years [2].The most common camera fingerprint is the photo-response nonuniformity (PRNU)[3] of the digital imaging sensor which is due to slight or minor variations in the properties of individual pixels, which produce a noise-like, yet deterministic pattern affecting every image taken by a sensor.

In the case of PRNU, the camera fingerprint is essentially a pattern with the same size as the imaging sensor. Thus it requires a large database to store those camera fingerprints in uncompressed format. In addition, the complexity of a particular fingerprint in a large database is also very high, typically requiring the computation of a correlation with each fingerprint in the database. The large scale problems, such as image classification, clustering or image retrieval problems based on camera identities, involve a huge number of PRNU patterns. Hence, these problems requires the techniques to efficiently store and query such databases. Another problem with PRNU fingerprints is that the test image should be geometrically aligned with the camera fingerprint stored in the database. Using the PRNU for large-scale image retrieval is an extremely challenging task. A possible solution is to provide several versions of the same fingerprint with different scale however at the cost of managing an even larger database.

In this paper, a novel technique is propose to reduce the size of camera fingerprints based on *random projections*. The technique is motivated by the Johnson-Lindenstrauss (JL) lemma [4], stating that a small set of points in a high dimensional space can be embedded into a lower dimensional space approximately preserving the distances between the points, and the recent results shows that random linear projections can provide such embeddings with high probability. In the case of PRNU fingerprints, it is easy to show that preserving the distance between two fingerprints is equivalent to preserving the angle between them. Since PRNU fingerprints of different sensors are known to be highly uncorrelated, and thus to form wide angles. As a consequence, in this paper the standard correlation detector is adapted to solve fingerprint matching and camera identification problems in the compressed domain.

As to practical issues, the complexity of randomly projecting a large fingerprint is greatly reduced by employing partial circulant matrices [5], which are known to be almost as good as fully random matrices. A binary version of the compressed fingerprint is proposed that further reduces storage and computational requirements.

2. BACKGROUND

There are large number of pictures uploaded, shared, and browsed by Internet users, resulting in very large collections of images that requires an efficient solutions for their management. An important task is the retrieval of pictures matching a specific criterion, that can be used for searching pictures of interest or for classifying similar photos. In this sense, content- based image retrieval is a technology that has received a lot of attention in recent years [2]. In a nutshell, it consists in extracting a set of representative features that allow to find pictures having similar content with respect to a query image. However, the content of a picture is not the sole criterion for performing image retrieval. Another very interesting task consists in looking for pictures that have been acquired by a specific device. Let us imagine a search engine that, given a specific camera as a query, returns all the web pages containing photos acquired by that camera. Such a technology could be very useful for detecting improper usage of images. The professional and expert photographers could use it to prevent improper diffusion and usage of their photos, large web sites could avoid being sued for redistributing unlicensed photographs, police investigators who have come across a digital camera or even the pictures which are linked to an unlawful act, e.g., child pornography, could look for other pictures taken by the same camera in either public databases or large internal databases managed by the police.

The authors propose a so-called *fingerprint digest*,[6] which works by keeping only a fixed number of the largest fingerprint values and their positions, so that the resulting database is independent of the sensor resolution. An improved search strategy based on fingerprint digest is proposed in [7]. An alternative solution is to represent sensor fingerprints in binary-quantized form [8]: even though the size of binary fingerprints scales with sensor resolution, binarization can considerably speed-up the fingerprint matching process.

3. PROPOSED TECHNIQUE

The system is modeled as in Fig. 1. A collection of photos is gathered, e.g., by means of an automatic web crawler, and an estimate of the fingerprint is extracted from each photo. This estimate is compressed by means of binary random projections and stored.

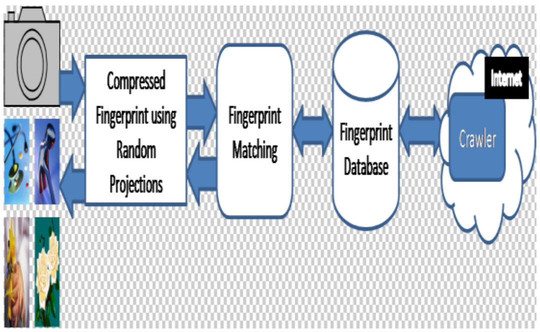

Fig.1. Block Diagram of the Proposed System.

PRNU databases can rapidly grow in size. For this reason, a method to "compress" them is required, with slight or ideally no information loss. One possible option is represented by *Random Projections* (RP), a low–complexity and yet powerful method for dimensionality reduction. The idea of RP is to project the original n–dimensional data to an m–dimensional subspace, with $m < n$, using a random matrix $\boldsymbol{\phi} \in R^{m \times n}$. Hence, a collection of N n–dimensional data $\mathbf{D} \in R^{n \times N}$ is reduced to an m–dimensional subspace $\mathbf{A} \in R^{m \times N}$ by

$$\mathbf{A} = \boldsymbol{\phi}\mathbf{D}.$$

The steps involved in this technique are :

3.1 Fingerprint Matching

In the fingerprint matching problem, a dictionary of fingerprints of N known cameras is constructed, which can be represented as a matrix $\mathbf{D} \in R^{n \times N}$. The goal of the classic fingerprint matching problem is finding the column that is most similar to a test fingerprint $\hat{\mathbf{k}} \in R^{n}$ that is presented to the system.

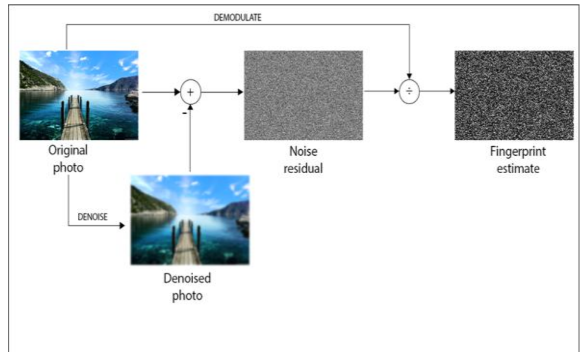

Fig.2. Camera Fingerprint Estimate

To this purpose, one of the most used similarity criteria is the correlation coefficient defined as follows:

$$\rho(\hat{\mathbf{k}}, \mathbf{d}_i) = \frac{(\hat{\mathbf{k}}, \mathbf{d}_i)}{||\hat{\mathbf{k}}||_2 ||\mathbf{d}_i||_2}, \quad i = 1, \ldots, N$$

To compress the database and test fingerprint representing them through a small number of random projections. This operation can be seen as the product times an $m \times n$ sensing matrix ϕ :

$$\mathbf{A} = \boldsymbol{\phi}\mathbf{D}$$

$$\mathbf{y} = \phi \hat{K}$$

Random projections can effectively reduce the dimension of the space the fingerprints live in thanks to the fact that they approximately preserve the geometry of the point cloud composed of the fingerprints. Since random projections approximately preserve the angle between any two fingerprints and since this angle is wide thanks to their incoherent nature, we can expect a compressive system to exhibit robust performance, while dramatically reducing the problem size. The system has to store the compressed dictionary $\mathbf{A}$ and a way to generate the compressed fingerprint whenever a test pattern is presented, using the same ϕ.

The first system design challenge is the choice of the sensing matrix: the most studied sensing matrices are made of realizations of independent and identically distributed (i.i.d.) Partial circulant matrices generate the first row $\boldsymbol{\varphi}$ at random and all the other rows are just circularly shifted versions of the first row. Circulant matrices provide great advantages because only the first row must be generated at random, and because fast multiplication is available through the FFT. Thanks to the use of the FFT, the product $\boldsymbol{\phi}\mathbf{D}$ can be implemented with $O(Nn \log n)$ operations instead of $O(Nmn)$. Consider the case of binary random measurements obtained as:

$$\mathbf{A} = \mathrm{sign}(\boldsymbol{\phi}\mathbf{D})$$

3.2 Camera Identification

The camera identification problem is conceptually very similar to the fingerprint matching scenario. The main difference is that a single test image is available instead of a set of them. Chen *et al.* [9] showed that the optimal detector for this problem correlates the noise residual of the image with a modulated version of the fingerprint stored in the database, where the modulating term is the test image. Extending this detector to the compressed domain is not possible because of the element wise product between test image and the fingerprint in the database. Instead, we investigate the performance of two simplified detectors that can be readily mapped to the compressed domain. The first simplified detector correlates the noise residual $\mathbf{w}$ of the test image with the camera fingerprint stored in the database. Essentially this system is capable of eliminates the modulating effect of the test image, thus it will be sub-optimal unless the test image is a constant pattern. It is sufficient to apply the sensing matrix to both noise residual and fingerprint to translate this detector to the compressed domain.

$$\rho(\mathbf{w}, \mathbf{d}_i) \longrightarrow \rho(\boldsymbol{\phi}\mathbf{w}, \boldsymbol{\phi}\mathbf{d}_i)$$

The second simplified detector considers the use of a fingerprint estimate $\mathbf{k}$ extracted from the single test image instead of the noise residual. The detector then correlates this test fingerprint estimate with the fingerprint stored in the dictionary.

$$\rho(\hat{\mathbf{k}}, \mathbf{d}_i) \longrightarrow \rho(\boldsymbol{\phi}\hat{\mathbf{k}}, \boldsymbol{\phi}\mathbf{d}_i).$$

3.3 Detection Metrics

The matching problem is concerned with finding the column of the dictionary that best matches a test compressed pattern. The test compressed fingerprint undergoes a binary hypothesis test for each column of the compressed dictionary. The two hypotheses are defined as:

H0: the compressed test fingerprint and the reference are not from the same camera

H1: the compressed test fingerprint and the reference are from the same camera

Reject the null hypothesis whenever the correlation coefficient is above a predefined threshold τ .

The following events, referring to a single instance of the hypothesis testing problem, *i.e.*,a single column of the dictionary. These are standard definitions, used for example in [10].

- **False Alarm**: the null hypothesis was incorrectly rejected.
- **Detection**: the null hypothesis was correctly rejected.

False alarm corresponds to the case in which the current column of the dictionary is the compressed fingerprint of a different camera with respect to the compressed fingerprint under test, but a match is incorrectly declared. On the other hand, *detection* occurs when the current column of the dictionary is the compressed fingerprint of the same camera as the compressed fingerprint under test, and a match is correctly declared.

Since previously-defined events are restricted to a single column of the dictionary, global events are introduced considering the dictionary as a whole.

• **False Acceptance**: the null hypothesis was rejected for at least one wrong camera.

True Detection: the null hypothesis was rejected only for the correct camera.

False acceptance corresponds to the case in which all the columns of the dictionary are tested, and at least one column containing the compressed fingerprint of a different camera with respect to the compressed fingerprint under test is declared as a match. On the other hand, *true detection* occurs when all the columns of the dictionary are tested, and a match is declared *only* for the column corresponding to the same camera of the compressed fingerprint under test.

4. Result

The performance of the compressed system is tested under various conditions. Experimental tests have confirmed the validity of the proposed method. From this perspective, random projections are significantly better than the other existing methods because they can provide higher compression ratios and improved scalability,

5. Conclusion

In this paper, an image retrieval problem is addressed where the user wants to find all the photos in a collection acquired by a specific device. PRNU fingerprints are an established method for robust camera identification, but their size makes them impractical to use on large scales. Random Projections can effectively compress the fingerprints and enable fast matching techniques that are suitable for huge collections of photos at a small cost in terms of detection performance. Moreover, the results suggest that the proposed techniques enable image retrieval based on camera identities on unprecedented scales, effectively paving the way to the realization of a camera search engine spanning huge image collections available on the Internet. Random Projections can effectively preserve the geometry of the database and significantly reduce the dimension of the problem with small penalties. The usage of real-valued and binary random measurements is characterized from a theoretical point of view in terms of the detection and false alarm probabilities. The use of random projections for compression of camera fingerprints paves the way to many interesting applications involving maintaining large databases of fingerprints or applications requiring transmission of fingerprints over band limited channels. From this perspective, random projections are significantly better than the other existing methods because they can provide higher compression ratios and improved scalability,

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