A Hybrid Approach to Video Source Identification

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Abstract

Multimedia Forensics allows to determine whether videos or images have been captured with the same device, and thus, eventually, by the same person. Currently, the most promising technology to achieve this task, exploits the unique traces left by the camera sensor into the visual content. Anyway, image and video source identification are still treated separately from one another. This approach is limited and anachronistic if we consider that most of the visual media are today acquired using smartphones, that capture both images and videos. In this paper we overcome this limitation by exploring a new approach that allows to synergistically exploit images and videos to study the device from which they both come. Indeed, we prove it is possible to identify the source of a digital video by exploiting a reference sensor pattern noise generated from still images taken by the same device of the query video. The proposed method provides comparable or even better performance, when compared to the current video identification strategies, where a reference pattern is estimated from video frames. We also show how this strategy can be effective even in case of in-camera digitally stabilized videos, where a non-stabilized reference is not available, by solving some state-of-the-art limitations. We explore a possible direct application of this result, that is social media profile linking, i.e. discovering relationships between two or more social media profiles by comparing the visual contents - images or videos - shared therein.

I. INTRODUCTION

Digital videos (DVs) are steadily becoming the preferred means for people to share information in an immediate and convincing way. Recent statistics showed a 75% increase in the number of DVs posted on Facebook in one year [1] and posts containing DVs yields more engagement than their text-only counterpart [2]. Interestingly, the vast majority of such contents are captured using smartphones, whose impact on digital photography is dramatic: in 2014, compact camera sales dropped by 40% worldwide, mostly because

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they are being replaced by smartphone cameras, which are always at your fingertips and makes sharing much easier [3].

In such a scenario, it is not surprising that digital videos gained importance also from the forensic and intelligence point of view: videos have been recently used to spread terror over the web, and many critical events have been filmed and shared by thousands of web users. In such cases, investigating the digital history of DVs is of paramount importance in order to recover relevant information, such as acquisition time and place, authenticity, or information about the source device. In the last decades Multimedia Forensics has developed tools for such tasks, based on the observation that each processing step leaves a distinctive trace on the digital content, as a sort of digital fingerprint. By detecting the presence, the absence or the incongruence of such traces it is possible to blindly investigate the digital history of the content [4].

In particular, the source identification problem - that is, univocally linking the digital content to the device that captured it - received great attention in the last years. Currently, the most promising technology to achieve this task exploits the detection of the sensor pattern noise (SPN) left by the acquisition device [5]. This footprint is universal (every sensor introduces one) and unique (two SPNs are uncorrelated even in case of sensors coming from two cameras of same brand and model). As long as still images are concerned, SPN has been proven to be robust to common processing operations like JPEG compression [5], or even uploading to social media platforms (SMPs) [6, 7].

On the contrary, research on source device identification for DVs is not as advanced. This is probably due to the higher computational and storage effort required for video analysis, the use of different video coding standards, and the absence of sizeable datasets available to the community for testing. Indeed, DV source identification borrowed both the mathematical background and the methodology from the still image case [8]: like for images, thus, assessing the origin of a DV requires the analyst to have either the source device or some training DVs captured by that device, from which to extract the reference SPN.

However, if we consider that 85% of shared media are captured using smartphones, which use the same sensor to capture both images and videos, it is possible to exploit images also for video source identification. A first hint in using still images to estimate the video fingerprint was recently provided in [9], where the authors noticed how image and video patterns of some portable devices acquiring non-stabilized video can be generally related by cropping and scaling operations. Anyway, in the research community, there’s still no better way to perform image and video source identification than computing two different reference SPNs, one for still images and one for videos respectively. In addition, a strong limitation is represented by the presence in many mobile devices of an in-camera digital video stabilization algorithm, such that a non-stabilized SPN reference cannot be estimated from a DV [8].

The first contribution of this work focuses on proposing a hybrid source identification approach, that exploits still images for estimating the fingerprint that will be used to verify the source of a video. The geometrical relation between image and video acquisition
processes are studied for 18 modern smartphones, including devices with in-camera digital stabilization. Secondly, we prove that the proposed technique, while preserving the state of the art performance for non-stabilized videos, is able to effectively detect the source of in-camera digitally stabilized videos also. Furthermore, this hybrid approach is used to link image and video contents belonging to different social media platforms, specifically Facebook and YouTube.

The rest of the paper is organized as follows: Section II introduces SPN based source device identification, and reviews the state of the art for DV source identification; Section III formalizes the considered problem and describes the proposed hybrid approach; Section IV presents the video dataset prepared for the tests, and discusses some YouTube/Facebook technical details related to the SPN; Section V is dedicated to the experimental validation of the proposed technique, including comparison with existing approaches, and tests on stabilized videos and on contents belonging to SMPs; finally, Section VI draws some final remarks and outlines future works.

Everywhere in this paper vectors and matrices are denoted in bold as $\mathbf{X}$ and their components as $X(i)$ and $X(i,j)$ respectively. All operations are element-wise, unless mentioned otherwise. Given two vectors $\mathbf{X}$ and $\mathbf{Y}$ we denote as $||\mathbf{X}||$ the euclidean norm of $\mathbf{X}$, as $\mathbf{X} \cdot \mathbf{Y}$ the dot product between $\mathbf{X}$ and $\mathbf{Y}$, as $\bar{X}$ the mean values of $\mathbf{X}$, as $\rho(s_1, s_2; \mathbf{X}, \mathbf{Y})$ the normalized cross-correlation between $\mathbf{X}$ and $\mathbf{Y}$ calculated as

$$\rho(s_1, s_2; \mathbf{X}, \mathbf{Y}) = \frac{\sum_i \sum_j (X(i,j) - \bar{X})(Y(i+s_1,j+s_2) - \bar{Y})}{||\mathbf{X} - \bar{X}|| ||\mathbf{Y} - \bar{Y}||}$$

If $\mathbf{X}$ and $\mathbf{Y}$ dimensions mismatch, a zero down-right padding is applied. Furthermore its maximum, namely the $\max_{s_1, s_2} \rho(s_1, s_2; \mathbf{X}, \mathbf{Y})$, is denoted as $\rho_{\text{peak}}(\mathbf{X}, \mathbf{Y}) = \rho(s_{\text{peak}}; \mathbf{X}, \mathbf{Y})$. The notations are simplified in $\rho(s_1, s_2)$ and in $\rho_{\text{peak}}$ when the two vectors cannot be misinterpreted.

II. DIGITAL VIDEO SOURCE DEVICE IDENTIFICATION BASED ON SENSOR PATTERN NOISE

The task of blind source device identification has gathered great attention in the multimedia forensics community. Several approaches were proposed to characterize the capturing device by analyzing traces like sensor dust [10], defective pixels [11], color filter array interpolation [12]. A significant breakthrough was achieved when Lukas et al. first introduced the idea of using Photo-Response Non-Uniformity (PRNU) noise to univocally characterize camera sensor [5]. Being a multiplicative noise, PRNU cannot be effectively removed even by high-end devices; moreover, it remains in the image even after JPEG compression at average quality. The suitability of PRNU-based camera forensics for images retrieved from common SMPs has been investigated in [6], showing that modifications applied either by the user or by the SMP can make the source identification based on PRNU ineffective. The problem of scalability of SPN-based camera identification
has been investigated in several works [13, 14]. Noticeably, in [13] authors showed that the Peak-to-Correlation Energy (PCE) provides a significantly more robust feature compared to normalized correlation. The vast interest in this research field fostered the creation of reference image databases specifically tailored for the evaluation of source identification [15], allowing a thorough comparison of different methods [16]. Recently, authors of [17] addressed the problem of reducing the computational complexity of fingerprint matching, both in terms of time and memory, through the use of random projections to compress the fingerprints, at the price of a small reduction in matching accuracy.

All the methods mentioned so far have been thought for (and tested on) still images. Although research on video source identification began almost at the same time, the state of the art is much poorer. In their pioneering work [8], Chen et al. proposed to extract the SPN from each frame separately and then merge the information through a Maximum Likelihood Estimator; as to the fingerprint matching phase, the PCE was recommended [8]. The experimental results showed that resolution and compression have an impact on performance, but identification is still possible if the number of considered frames can be increased (10 minutes for low resolution, strongly compressed videos). Two years later, Van Houten et al. investigated the feasibility of camcorder identification with videos downloaded from YouTube [18], yielding encouraging results: even after YouTube recompression, source identification was possible. However, results in [18] are outdated, since both acquisition devices and video coding algorithms have evolved significantly since then. This study was extended by Scheelen et al. [19], considering more recent cameras and codecs. Results confirmed that source identification is possible, however authors clarify that the reference pattern was extracted from reference and natural videos before re-encoding. Concerning reference pattern estimation, Chuang et al. [20] firstly proposed to treat differently the SPN extracted from video frames based on the type of their encoding; the suggested strategy is to weigh differently intra- and inter- coded frames, based on the observation that intra-coded frames are more reliable for PRNU fingerprint estimation, due to less aggressive compression. A recent contribution from Chen et al. [21] considered video surveillance systems, where the videos transmitted over an unreliable wireless channel, can be affected by blocking artifacts, complicating pattern estimation.

Most of the research on video forensics neglects the analysis of digitally stabilized videos, where the SPN can be hardly registered. In [22] an algorithm was proposed to compensate the stabilization on interlaced videos. Anyway, the method was tested on a single device and it is inapplicable on the vast majority of modern devices, that come to life with a 1080p camera (p stands for progressive). Recently, Taspinar et al. [9] showed that digital stabilization applied out of camera by a third party program can be managed by registering all video frame on the first frame based on rotation and scaling transformation. Anyway the technique is proved to be really effective only when a reference generated from non-stabilized videos is available. This is a gap to be filled considering that most modern smartphones features in-camera digital stabilization, and that in many cases such feature cannot be disabled.
As the reader may have noticed, all the mentioned works discuss source identification either for still images or videos (with the only exception of [9]), and in the vast majority of cases the reference pattern is estimated from “clean” contents, meaning images or frames as they exit from the device, without any alteration due to re-encoding or (even worse) upload/download from SMPs. This approach seriously limits the applicability of source device identification, since it assumes that either the device or some original content is available to the analyst. In the following sections we show how to exploit the available mathematical frameworks to determine the source of a DV based on a reference derived by still images, even in the case of in-camera digitally stabilized videos, and eventually apply this strategy to link images and video from different SMPs.

III. Hybrid Sensor Pattern Noise Analysis

Digital videos are commonly captured at a much lower resolution than images: top-level portable devices reach 4K video resolution at most (which means, 8 Megapixels per frame), while the same devices easily capture 20 Megapixels images. During video recording, a central crop is carried so to adapt the sensor size to the desired aspect ratio (commonly 16:9 for videos), then the resulting pixels are scaled so to match exactly the desired resolution (see Figure 1). As a direct consequence, the sensor pattern noise extracted from images and videos cannot be directly compared and most of the times, because of cropping, it is not sufficient to just scale them to the same resolution. The hybrid source identification (HSI) process consists in identifying the source of a DV based on a reference derived from still images. The strategy involves two main steps: i) the reference fingerprint is derived from still images acquired by the source device; ii) the query fingerprint is estimated from the investigated video and then compared with the reference to verify the possible match.

The camera fingerprint $K$ can be estimated from $N$ images $I^{(1)}, \ldots, I^{(N)}$ captured by the source device. A denoising filter [5, 23] is applied to each frame and the noise residuals $W^{(1)}, \ldots, W^{(N)}$ are obtained as the difference between each frame and its denoised version.
Then the fingerprint estimation $\mathbf{K}$ is derived by the maximum likelihood estimator [24]:

$$\mathbf{K} = \frac{\sum_{i=1}^{N} W^{(i)} I^{(i)}}{\sum_{i=1}^{N} (I^{(i)})^2}.$$  \hspace{1cm} (1)

The fingerprint of the video query is estimated in the same way by the available video frames.

Denoting by $\mathbf{K}_R$ and $\mathbf{K}_Q$ the reference and query fingerprints, the source identification is formulated as a two-channel hypothesis testing problem [25]:

$$H_0 : \mathbf{K}_R \neq \mathbf{K}_Q$$
$$H_1 : \mathbf{K}_R = \mathbf{K}_Q.$$ 

where $\mathbf{K}_R = \mathbf{K}_R + \Xi_R$ and $\mathbf{K}_Q = \mathbf{K}_Q + \Xi_Q$, being $\Xi_R$ and $\Xi_Q$ noise terms. In the considered case, $\mathbf{K}_R$ and $\mathbf{K}_Q$ are derived from still images and video frames respectively, thus differing in resolution and aspect ratio due to the cropping and resize occurring during the acquisition (see Fig. 1). Then, the test statistic is built as proposed in [26], where the problem of camera identification from images that were simultaneously cropped and resized was studied: the two-dimensional normalized cross-correlation $\rho(s_1, s_2)$ is calculated for each of the possible spatial shifts $(s_1, s_2)$ determined within a set of feasible cropping parameters. Then, given the peak $\rho_{\text{peak}}$, its sharpness is measured by the Peak to Correlation Energy (PCE) ratio [13] as

$$\text{PCE} = \frac{\rho(s_{\text{peak}})}{\frac{1}{mn - |N|} \sum_{s \not\in N} \rho(s)}$$ \hspace{1cm} (2)

where $N$ is a small set of peak neighbors.

In order to consider the possible different scaling factors of the two fingerprints - since videos are usually resized - a brute force search can be conducted considering the PCE as a function of the plausible scaling factors $r_0, \ldots, r_m$. Then its maximum

$$P = \max_{r_i} \text{PCE}(r_i)$$ \hspace{1cm} (3)

is used to determine whether the two fingerprints belong to the same device. Practically, if this maximum overcomes a threshold $\tau$, $H_1$ is decided and the corresponding values $s_{\text{peak}}$ and $r_{\text{peak}}$ are exploited to determine the cropping and the scaling factors. In [26] it is shown that a theoretical upper bound for False Alarm Rate (FAR) can be obtained as

$$\text{FAR} = 1 - (1 - Q(\sqrt{\tau}))^k$$ \hspace{1cm} (4)

where $Q$ is the cumulative distribution function of a normal variable $N(0,1)$ and $k$ is the number of tested scaling and cropping parameters.

This method is expected to be computationally expensive, namely for large dimension images. Anyway, this problem can be mitigated considering that:
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- if the source device is available, or its model is known, the resize and cropping factors are likely to be determined by the camera software specifics or by experimental testing;
- even when no information about the model is available, it is not necessary to repeat the whole search on all frames. Once a sufficiently high correlation is found for a given scale, the search can be restricted around it.

In Section IV, cropping and scaling factors for 18 devices are reported.

i. Source Identification of Digitally Stabilized Videos

Recent camera softwares include digital stabilization technology to reduce the impact of shaky hands on captured videos. By estimating the impact of the user movement the software adjusts which pixels on the camcorder’s image sensor are being used. Image stabilization can be usually turned on and off by the user on devices based on Android OS while in iOS devices this option cannot be modified by the camera software. The source identification of videos captured with active digital stabilization cannot be accomplished based on the PRNU fingerprint: in fact the process disturbs the fingerprints alignment that is a sine qua non condition for the identification process. HSI solves the problem on the reference side (the fingerprint is estimated from still images) but the issue remains on the query side. A first way to compensate digital stabilization was proposed in [27] and tested on a single Sony device. Recently, in [9], it was proposed to compute the fingerprint from a stabilized video by using the first frame noise as reference and by registering all following frame noises on the first one by estimating the similarity transformation that maximize the correlation between the two patterns. The technique was proved to compensate digital stabilization applied out of camera by third party software, but with limited reliability. HSI allows to intuitively perform source identification of stabilized videos: on the reference side, still images are exploited to estimate a reliable, stable fingerprint, while on the query side, each video frame is registered on the image reference based on a similarity transformation. In Section iii we will prove the effectiveness of this technique by estimating the fingerprint with only five frames on in-camera stabilized videos from modern devices. In the next section we define the hybrid source identification pipeline conceived to reduce false alarm and computational effort.

ii. HSI Pipeline

Given a query video and a set of images belonging to a reference device, the proposed pipeline is summarized in Fig. 2. First, the device fingerprint $K_I$ is estimated from still images according to Eq. (1). Then, stabilized videos are preliminary identified by splitting the frames in two groups that are used independently to estimate two different fingerprints, as described in [9], and computing their PCE; a low PCE value will expose the presence of digital stabilization. If no stabilization is detected, the video fingerprint $K_V$ is just estimated treating video frames as still images. Conversely, each frame is
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Figure 2: HSI pipeline to source attribution of a query video.
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registered on the reference $K_I$ searching the plausible parameters based on PCE values. In case the expected range of parameters are known, the search can be reduced to save computational effort and mitigate the false alarm (see Section ii for details). Only the registered video frames overcoming a PCE threshold $\tau$ are then aggregated to estimate the video fingerprint $K_V$. Once both fingerprints $K_I$ and $K_V$ are available, they are compared according to Eq. (3) by testing plausible scaling factors. Again, the analysis can be reduced to expected cropping and scaling factors.

iii. Extension to contents shared on social media platforms

The proposed technique can be applied to match multimedia contents exchanged through different SMPs. Let us consider a user publishing, with an anonymous profile, videos with criminal content through a SMP. At the same time this user, say Bob, is leading his virtual social life on another social network where he publicly shares his everyday’s pictures. Unaware of the traces left by the sensor, he captures with the same device the contents he shares on both profiles. Then, the fingerprints derived from the images and videos on the two social platforms can be compared with the proposed method to link Bob to the criminal videos.

Noticeably, analyzing multimedia content shared on SMPs is not a trivial task. Indeed, besides stripping all metadata, SMPs usually re-encode images and videos. For example, Facebook policy is to down-scale and re-compress images so to obtain a target bit-per-pixel value [28]; Youtube also scales and re-encodes digital videos [29]. Needless to say, forensic traces left in the signal are severely hindered by such processing. Sensor pattern noise, however, is one of the most robust signal-level features, surviving down-scaling followed by compression. Nevertheless, when it comes to link the SPN extracted from, say, a Youtube video and a Facebook image, a new problem arises: since both content have been scaled/cropped by an unknown amount, such transformation must be estimated in order to align the patterns.

Interestingly, the hybrid approach can be applied to this scenario. In Fig. 3 the geometric transformations occurring on the contents are summarized, starting from the full frame $F$; an image $F_{i1}$ is produced by the acquisition process from $F$ with scaling and cropping factors $s_{i1}$ and $c_{i1}$ respectively. The uploading process over the SMP applies a new transformation - with factors $s_{i2}$ and $c_{i2}$ - thus producing $F_{i2}$. In a similar way, the video $F_{v1}$ is generated from the camera and $F_{v2}$ is uploaded onto another SMP - with cropping and scaling factors of $s_{v1}$, $c_{v1}$ and $s_{v2}$, $c_{v2}$ respectively. It can be easily deduced that, for both native and uploaded contents, image and video fingerprints are linked by a geometric transformation consisting in a cropping and scaling operation. Then, the hybrid approach that we used to determine the transformation $t_{i1,v1}$ which aligns the fingerprints of two native contents can be also applied to determine $t_{i2,v2}$, thus directly linking $F_{i2}$ to $F_{v2}$.

Two main drawbacks are expected for this second application. Firstly the compared contents have been probably compressed twice and the SPN traces are likely deteriorated.
Figure 3: Geometric transformations applied to the sensor pattern from the full frame to the image and video outputs on both social media platforms.
Furthermore it may be hard to guess the right scaling and cropping parameters just from \( F_{I_2} \) and \( F_{V_2} \). In these cases, an exhaustive search of all plausible scaling and cropping factors is required. In Section II the proposed application is tested to link the images of a Facebook profile to the videos of a YouTube profile.

IV. Dataset for Hybrid Source Identification

We tested the proposed technique on an extensive dataset consisting of 1978 flat field images, 3311 images of natural scenes and 339 videos captured by 18 devices from different brands (Apple, Samsung, Huawei, Microsoft, Sony). YouTube versions of all videos and Facebook versions of all images (in both High and Low Quality) were also included. This dataset will be made available to the scientific community. In the following we detail the dataset structure.

i. Native contents

We considered 18 different modern devices, both smartphones and tablets. Pictures and videos have been acquired with the default device settings that, for some models, include the automatic digital video stabilization. In Table I we reported the considered models, their standard image and video resolution and whether the digital stabilization was active on the device. From now on we’ll refer to these devices with the names C1, . . . , C18 as defined in the Table II. For each device we collected at least:

- Reference side: 100 flat-field images depicting skies or walls; 150 images of indoor and outdoor scenes; 1 video of the sky captured with slow camera movement, longer than 10 seconds
- Query Side: videos of flat textures, indoor and outdoor scenes. For each of the video categories (flat, indoor and outdoor) at least 3 different videos have been captured considering various scenarios: i) still camera, ii) walking operator and iii) panning and rotating camera. We’ll refer to them as still, move and panrot videos respectively. Thus, each device has at least 9 videos, each one lasting more than 60 seconds.

ii. Facebook and YouTube sharing platforms

Images have been uploaded on Facebook in both low quality (LQ) and high quality (HQ). The upload process eventually downscales the images depending on their resolutions and selected quality. Videos have been uploaded to YouTube through its web application and then downloaded through Clip Grab selecting the best available resolution.

[1] https://lesc.dinfo.unifi.it/en/datasets
[2] The metadata orientation has been removed from all of the images and videos to avoid unwanted rotation during the contents upload.
Table 1: Considered devices with their default resolution settings for image and video acquisition.

| ID | model                  | image resolution | video resolution | digital stab |
|----|------------------------|------------------|-----------------|--------------|
| C1 | Galaxy S3              | 3264 × 2448      | 1920 × 1080     | off          |
| C2 | Galaxy S3 Mini         | 2560 × 1920      | 1280 × 720      | off          |
| C3 | Galaxy S3 Mini         | 2560 × 1920      | 1280 × 720      | off          |
| C4 | Galaxy S4 Mini         | 3264 × 1836      | 1920 × 1080     | off          |
| C5 | Galaxy Tab 3 10.1      | 2048 × 1536      | 1280 × 720      | off          |
| C6 | Galaxy Tab A 10.1      | 2592 × 1944      | 1280 × 720      | off          |
| C7 | Galaxy Trend Plus      | 2560 × 1920      | 1280 × 720      | off          |
| C8 | Ascend G6              | 3264 × 2448      | 1280 × 720      | off          |
| C9 | Ipad 2                 | 960 × 720        | 1280 × 720      | off          |
| C10| Ipad Mini              | 2592 × 1936      | 1920 × 1080     | on           |
| C11| Iphone 4s              | 3264 × 2448      | 1920 × 1080     | on           |
| C12| Iphone 5               | 3264 × 2448      | 1920 × 1080     | on           |
| C13| Iphone 5c              | 3264 × 2448      | 1920 × 1080     | on           |
| C14| Iphone 5c              | 3264 × 2448      | 1920 × 1080     | on           |
| C15| Iphone 6               | 3264 × 2448      | 1920 × 1080     | on           |
| C16| Iphone 6               | 3264 × 2448      | 1920 × 1080     | on           |
| C17| Lumia 640              | 3264 × 1840      | 1920 × 1080     | off          |
| C18| Xperia Z1c             | 5248 × 3936      | 1920 × 1080     | on           |

V. Experimental validation

The experimental section is split in four parts, each focused on a different contribution of the proposed technique:

1. we determine the cropping and scaling parameters applied by each device model;

2. we verify that, in the case of non-stabilized video, the performance of the hybrid approach is comparable with the source identification based on a video reference;

3. we show the effectiveness in identifying the source of in-camera digitally stabilized videos;

4. we show the performance in linking Facebook and YouTube profiles.

i. Fingerprints matching parameters

The scaling and cropping factors applied by each device were derived by registering the reference video fingerprint $\tilde{K}_V$ on a reference fingerprint $\tilde{K}_I$ derived from still images according to the P statistic (Eq. 3). For each device we estimated $\tilde{K}_I$ by means of 100 images randomly chosen from the flat-field pictures. For non-stabilized videos, $\tilde{K}_V$ was derived by means of the first 100 frames of the reference video available for that device. In Table 2 we reported the obtained cropping parameter (in terms of coordinates of the...
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upper-left corner of the cropped area along $x$ and $y$ axes, whereas the right down corner is derived by the video size) and the scaling factor, maximising the PCE. For instance, C1 image fingerprint should be scaled with a factor 0.59 and cropped on the upper left side of 307 pixels along the $y$ axis to match the video fingerprint; C9 is a pretty unique case in which the full frame is applied for video and is left and right cropped of 160 pixels to capture images.

Table 2: Rescaling and cropping parameters that link image and video SPNs for the considered devices, in absence of in-camera digital stabilization.

| ID | scaling | central crop along $x$ and $y$ axes |
|----|---------|-------------------------------------|
| C1 | 0.59    | [0 307]                             |
| C2 | 0.5     | [0 228]                             |
| C3 | 0.5     | [0 228]                             |
| C4 | 0.59    | [0 0]                               |
| C5 | 1       | [408 354]                           |
| C6 | 0.49    | [0 246]                             |
| C7 | 0.5     | [0 240]                             |
| C8 | 0.39    | [0 306]                             |
| C9 | 1       | [-160 0]                            |
| C17| 0.59    | [0 1]                               |

In case of stabilized video, the cropping and scaling factors varies in time with possible rotation applied too. For these devices we thus determined the registration parameters of the first 10 frames of the available video reference; the main statistics are reported in Table 3.

Table 3: Rescaling and cropping parameters that link image and video SPNs for the considered devices using in-camera digital stabilization. The values are computed on the first 10 frames of the available video reference; min, median (bold), and max values are represented.

| ID | scaling | central crop along $x$ and $y$ rotation (CCW) |
|----|---------|-----------------------------------------------|
| C10| [0.806 | 0.815 0.821] [243 256 261] [86 100 103] [-0.2 0 0.2] |
| C11| [0.748 | 0.750 0.753] [380 388 392] [250 258 265] [-0.2 0 0.2] |
| C12| [0.684 | 0.689 0.691] [287 294 304] [135 147 165] [-0.2 0 0.6] |
| C13| [0.681 | 0.686 0.691] [301 318 327] [160 181 195] [-0.4 0 1] |
| C14| [0.686 | 0.686 0.689] [261 301 304] [119 161 165] [-0.4 0 0] |
| C15| [0.696 | 0.703 0.713] [298 322 345] [172 190 218] [-0.2 0.2 1.6] |
| C16| [0.703 | 0.706 0.708] [315 323 333] [178 187 201] [-0.2 0.2 0.4] |
| C18| [0.381 | 0.384 0.387] [548 562 574] [116 121 126] [0 0 0] |

These data can be exploited to reduce the parameter search space in case of source identification of digitally stabilized videos. Indeed, an exhaustive search of all possible
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scaling and rotation parameters, required in a blind analysis, would be infeasible on large scale: in our tests a totally blind search can take up to 10 minutes per frame on a standard computer, while the informed search reduces the time to less than a minute for stabilized videos and a few seconds for non-stabilized videos.

ii. HSI Performance

In this section we compare the proposed technique with the state of the art approach, where the fingerprint is derived estimating the SPN from a reference video. The comparison is only meaningful for non-stabilized devices. For each device, the reference fingerprints $\tilde{K}_I$ and $\tilde{K}_V$ were derived respectively from the first 100 natural reference images (for the proposed method) and from the first 100 of the reference video (for the video reference approach). Given a video query, the fingerprint to be tested was derived by the first 100 frames and compared with $\tilde{K}_V$ and with $\tilde{K}_I$ adopting the cropping and scaling parameters expected for the candidate device (Eq. 2). We refer to the test statistics as $P_V$ and $P_I$ to distinguish the reference origin (video frames or still images). For each device we tested all available matching pairs (reference and query from the same source device) and an equal number of mismatching pairs (reference and query from different source devices) randomly chosen from all available devices. We refer to these statistics as $mP_I$ and $mP_V$ respectively (for video references). In Fig. 4 we report for each device: i) the statistics $mP_I$ and $mP_V$ (blue and pink respectively) of matching pairs; ii) $mmP_I$ and $mmP_V$ (in red), the statistics for mismatching cases. The plot shows that distributions can be perfectly separated when the reference is estimated from images (100% accuracy), while in the video reference case the accuracy is 99.5%, confirming that the performance are comparable.

iii. HSI Performance on Stabilized Videos

State of the art results in identifying the source of a stabilized video are provided in [9]. The authors, based on a similar registration protocol, analyze the performance using both non-stabilized and stabilized references. Their results are reported in Table 4 for convenience: we see that, if a non-stabilized reference is available, the method achieves a true positive rate 0.83. Unfortunately in several modern devices (e.g., Apple smartphones) digital stabilization cannot be turned off without third party applications; in this case, only stabilized reference can be exploited, achieving a TPR of 0.65.

In the following, we will show that exploiting the proposed HSI method, this performance drop can be solved. For each device, the reference fingerprints $\tilde{K}_I$ was estimated from 100 natural images. Given a video query, each frame is registered on $\tilde{K}_I$ searching within the expected parameters for the candidate device (as derived in Section i). The video fingerprint $\tilde{K}_V$ is then obtained by aggregating all registered video frames whose PCE wrt $\tilde{K}_I$ overcomes the aggregation threshold $\tau$. Finally, the aggregated fingerprint $\tilde{K}_V$ is compared with the reference SPN $\tilde{K}_I$. All tests were performed limiting the analysis to the first 5 frames of each video. For each device, we tested all available matching videos.
A Hybrid Approach to Video Source Identification

Figure 4: (Best viewed in colors) Matching statistics $m_P^I$ and $m_P^V$ are represented by the blue and pink boxplots, respectively. Correspondent mismatching statistics in red. On each box, the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers denote the minimum and maximum of the statistics. For plotting purposes, we defined $\log(a) = -\infty$ if $a \leq 0$.

Table 4: Performance of Source Identification of digitally stabilized video (using ffmpeg) using both non-stabilized and stabilized references reported in [9].

| Reference       | Query     | TPR  | FPR |
|-----------------|-----------|------|-----|
| Non-stabilized  | Stabilized| 0.83 | 0   |
| Stabilized      | Stabilized| 0.65 | 0   |

and an equal number of mismatching videos randomly chosen from all available devices. In Figure 5 we show the system accuracy by varying the aggregation threshold $\tau$. Table 5 shows, for different values of $\tau$, the the TPR and FPR corresponding to the best accuracy. Fig. 6 shows the matching and mismatching PCE statistics obtained using $\tau = 38$. Results clearly show that, using $\tau = 50$, the system achieves a TPR equal to 0.83, which is totally consistent with results achieved in [9], but in our case without the need for a non-stabilized video reference. Moreover, results show that using a slightly lower aggregation threshold some improvement can be achieved, (TPR 0.86 with an aggregation threshold of 38).
iv. Results on contents from SMPs

In this section we test the HSI approach in the application scenario of linking Facebook and YouTube accounts containing images and videos captured with the same device. For clarity we considered the non-stabilized and stabilized cases separately. Furthermore, we conducted two experiments: one estimating the SPN from images uploaded to Facebook using the high-quality option, and another experiment estimating the SPN from images uploaded using the low quality option. A detailed explanation of the differences between the two options is given in [28], here we only mention the fact that under low-quality upload images are downsampled so that their maximum dimension does not exceed 960 pixels, while under high-quality upload the maximum allowed dimension rises to 2048 pixels. Throughout all tests, we used 100 images for estimating the camera fingerprint.
### Table 5: Performance of the proposed method for different values of the aggregation threshold $\tau$.

| Aggregation threshold ($\tau$) | Accuracy | TPR  | FPR  | AUC  |
|-------------------------------|----------|------|------|------|
| 30                            | 89%      | 0.79 | 0.02 | 0.93 |
| 32                            | 89%      | 0.82 | 0.05 | 0.94 |
| 34                            | 90%      | 0.84 | 0.03 | 0.94 |
| 36                            | 93%      | 0.87 | 0.01 | 0.95 |
| 38                            | 93%      | 0.86 | 0.0  | 0.94 |
| 40                            | 93%      | 0.87 | 0.01 | 0.93 |
| 42                            | 93%      | 0.85 | 0    | 0.93 |
| 44                            | 93%      | 0.85 | 0    | 0.93 |
| 46                            | 93%      | 0.85 | 0    | 0.93 |
| 48                            | 92%      | 0.84 | 0    | 0.92 |
| 50                            | 92%      | 0.83 | 0    | 0.92 |
| 52                            | 91%      | 0.82 | 0    | 0.91 |
| 54                            | 91%      | 0.82 | 0    | 0.91 |

**Figure 6:** (Best viewed in colors) Details of the performance achieved with best aggregation threshold (38) on native stabilized videos. Matching and mismatching statistics are reported in blue and red, respectively, for each device.

After estimating image and video fingerprints according to the method described in previous sections, we investigated the matching performance by varying the number of frames employed to estimate the fingerprint of the query video. For sake of simplicity we reported the aggregated results with a ROC curve where true positive rate and false
alarm rate are compared, and we used the AUC as an overall index of performance. Similarly to the previous experiment, we considered all available matching videos for each device (minimum 9 videos, 17 on average) and an equal number of randomly selected mismatching videos. In Fig. 7 we report the results of the first experiment (high quality Facebook reference vs YouTube non-stabilized videos) by using 100, 300 and 500 frames to estimate the fingerprint from the video. It can be easily noticed that a hundred frames is rarely enough to correctly link two profiles. Moving from 100 to 300 frames significantly improves the performance, and much slighter improvement can be achieved passing from 300 to 500 frames. The AUC values for the three cases are 0.67, 0.86, 0.88, respectively.

![YouTube VS Facebook (HQ)](image)

**Figure 7:** (Best viewed in colors) ROC curve for profile linking between non-stabilized YouTube videos and Facebook HQ images by varying the number of frames to estimate the video reference.

When Facebook images uploaded in low quality are used as reference, the estimated pattern is expected to be less reliable than for the high quality case. This degradation on the reference side can be mitigated by using more robust estimates on the query side; for this reason, for the low quality case, we also considered using 500, 800 and 1000 frames for extracting the query pattern, achieving ROC curves reported in Fig. 8. The corresponding AUC values are 0.57, 0.70, 0.75, 0.83 and 0.86 using 100, 300, 500, 800 and 1000 frames respectively.
Let us now focus on the case of in-camera stabilized videos downloaded from Youtube. Fig. 5 reports the achieved performance for different values of the aggregation threshold $\tau$. The plot suggests that using $\tau = 38$ remains the best choice also in this experiment, leading to 87.3% overall accuracy. Fig. 9 details the performance for each device by applying such aggregation threshold. Thus, we can say that the hybrid approach to source identification provides promising results for linking SMP profiles even in the case of in-camera digitally stabilized videos.

VI. Conclusions

In this paper we proposed an hybrid approach to video source identification using a reference fingerprint derived from still images. We showed that the hybrid approach yields comparable or even better performance than the current strategy of using a video reference in the case of non-stabilized videos. As a major contribution, our approach allows reliable source identification even for videos produced by devices that enforce digital in-camera stabilization (e.g., all recent Apple devices), for which a non-stabilized reference is not available. We reported the geometrical relationships between image
and video acquisition process of 18 different devices, even in case of digitally stabilized videos. The proposed method was applied to link image and video contents belonging to different social media platforms: its effectiveness has been proved to link Facebook images to YouTube videos, with promising results even in the case of digitally stabilized videos. Specifically, when low quality Facebook images are involved, we showed that some hundreds of video frames are required to effectively link the two sensor pattern noises. We performed experiments on an brand new dataset of 339 videos and 5289 images from 18 different modern smartphones and tablets, each accompanied by its Facebook and YouTube version. The dataset will be shared with the research community to support advancements on these topics. The main limitation of the proposed approach is the need for a brute force search for determining scale (and, in the case of stabilized devices, rotation) when no information on the tested device is available. A possible way to mitigate this problem would be to design SPN descriptors that are simultaneously invariant to crop and scaling. This challenging task is left for future work.

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