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LETTER

Rotation-Tolerant Camera Identification Using Optimal Tradeoff Circular Harmonic Function Correlation Filter

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SUMMARY In this paper, we propose a novel camera identification method based on photo-response non-uniformity (PRNU), which performs well even with rotated videos. One of the disadvantages of the PRNU-based camera identification methods is that they are very sensitive to de-synchronization. If a video under investigation is slightly rotated, the identification process without synchronization fails. The proposed method solves this kind of out-of-sync problem, by achieving rotation-tolerance using Optimal Tradeoff Circular Harmonic Function (OTCHF) correlation filter. The experimental results show that the proposed method identifies source device with high accuracy from rotated videos.

key words: *camera identification, PRNU, circular harmonic function, optimal trade-off filter, correlation filter*

1. Introduction

Ever since analog imaging devices have been replaced by their digital counterparts, there has been an increasing demand for a series of reliable multimedia forensic algorithms [1]. One of the important forensic algorithms is to establish the origin of digital videos. These algorithms can be employed to arrest child pornography filmmakers or movie pirates.

Among methods that have been developed in this field, the photo-response non-uniformity (PRNU) based methods are actively being studied [2]–[8]. The PRNU is an intrinsic property of all digital imaging sensors due to slight variations among individual pixels in their ability to convert photons to electrons. This PRNU plays the role of a sensor fingerprint which can be used for device identification. Lukas et al. first introduced the PRNU-based camera identification method [2]. And they extended their method to identify digital cameras from video clips [3]. Hyun et al. proposed a camera identification method for heavily compressed low resolution videos [4]. Their method transforms the reference PRNU to the form of a minimum average correlation energy (MACE) filter to perform well with heavily compressed low resolution videos. Li attenuated the influence of details from scenes on PRNUs in order to improve the accuracy of the identifier [5].

(a) (b)

Fig. 1 Example of rotation attack: (a) an original video and (b) a video rotated by 1°.

The PRNU-based methods have numerous advantages and show high accuracy for device identification. Moreover, these methods are able to identify not only device manufacturers but also individual cameras between the same models. The PRNU-based methods, however, suffer from geometric distortion attacks such as scaling and rotation which spatially de-synchronize target PRNU with reference PRNU. If a video under investigation is slightly rotated or scaled, the detection process without synchronization fails.

Recently, several researchers have started to develop techniques to solve the out-of-sync problem by scaling. Goljan et al. solved this problem by calculating similarity for target PRNUs inverted by all scaling factors in the expected range [6]. Hyun et al. proposed a device identification method from up-scaled and cropped videos [7]. A scaling factor was estimated by using the periodic characteristic of resampling and the target PRNU was synchronized by inverting scale transform with the estimated factor. They also proposed a down-scale tolerant camera identification method [8].

In this paper, we deal with the out-of-sync problem using rotation. Figure 1 (b) shows a video rotated by 1°. In the native eye, it is difficult to recognize that the video is slightly rotated with only the information provided by the video. However, if this rotated video is investigated to identify source devices, the detection accuracy will be severely degraded. Consequently, attackers can make camera identification fail by this simple rotation attack. Therefore, we propose a rotation-tolerant camera identification method.

To solve the out-of-sync problem by rotation, we ex-

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ploit the OTCHF filter [9]. The OTCHF filter was successfully applied to many applications which are resilient to geometric distortions. Kim and Kumar proposed the rotation-tolerant watermark detection scheme by using the OTCHF filter. They achieved the rotation tolerance by the filter design procedure that utilizes the property of circular harmonic function and optimal trade off of output noise variance (ONV), average correlation energy (ACE), and average similarity measure (ASM) parameters [10]. In this paper, we apply the OTCHF filter to camera identification. In order to minimize the performance degradation caused by OTCHF transformation, we filtered the reference PRNU by sign function and designed appropriate range of rotation response of the OTCHF filter (See Sect. 3).

The rest of this paper is organized as follows. In Sect. 2, we describe the OTCHF correlation filter. Our camera identification method is presented in Sect. 3. Experimental results are shown in Sect. 4 and Sect. 5 concludes the paper.

2. Optimal Tradeoff Circular Harmonic Function Correlation Filter

In this section, we provide an overview of the optimal tradeoff circular harmonic function (OTCHF) correlation filter [9].

The OTCHF correlation filter is based on the circular harmonic function (CHF), given by the following pair of equation:

$$\begin{aligned} P(\rho,\phi) &= \sum_k P_k(\rho)e^{jk\phi} \\ P_k(\rho) &= \frac{1}{2\pi}\int_0^{2\pi} P(\rho,\phi)e^{-jk\phi}d\phi \end{aligned} \tag{1}$$

where $P(\rho,\phi)$ is 2-D Fourier transform (FT) of 2-D pattern in polar coordinates and $P_k(\rho)$ is the k-th CHF.

An important property of the CHF is its invariance to rotation changes. If the $p_\Theta(x,y)$ denotes a rotated version of 2-D pattern $p(x,y)$ by angle Θ in the clockwise direction, the k-th CHF of the 2-D polar FT of $p_\Theta(x,y)$ is expressed as follow:

$$P_{\theta k}(\rho) = P_k(\rho)e^{jk\theta} \tag{2}$$

where $P_k(\rho)$ is the k-th CHF of the 2-D polar FT of $p(x,y)$. Thus, the rotation operation only affects the CHF coefficient functions by a phase factor $e^{jk\theta}$.

If 2-D FT of input pattern is $F(u,v)$ and the correlation filter is $H(u,v)$, we obtain the following expression for the correlation value c between $F(u,v)$ and $H(u,v)$ in terms of CHF using Eq. (1).

$$\begin{aligned} c &= \int\int F(u,v)H^*(u,v)dudv \\ &= \int_0^{2\pi} d\phi \int_0^\infty \rho d\rho F(\rho,\phi)H^*(\rho,\phi) \\ &= \int_0^\infty \rho d\rho \int_0^{2\pi} d\phi \left[\sum_k F_k(\rho)e^{jk\phi} \times \sum_l H_l^*(\rho)e^{-jl\phi}\right] \\ &= \int_0^\infty \rho d\rho \int_0^{2\pi} d\phi \left[\sum_k \sum_l F_k(\rho)H_l^*(\rho)e^{(k-j)j\phi}\right] \end{aligned} \tag{3}$$

The integral $\int_0^{2\pi} e^{(k-l)j\phi}d\phi$ is zero for $k \neq l$, thus only a single summation is needed leading to the following simpler expression for the correlation output:

$$c = \sum_{k=-\infty}^{\infty} C_k \;\; where \; C_k = 2\pi \int_0^\infty F_k(\rho)H_k^*(\rho)\rho d\rho \tag{4}$$

The rotation invariance property described above can be used to decompose the correlation operation into a convenient form. Suppose the input pattern $f(x,y)$ is rotated by angle θ, we can rewrite Eq. (4) as a function of θ:

$$c(\theta) = \sum_{k=-\infty}^{\infty} C_k e^{jk\theta} \tag{5}$$

where C_k is the same as in Eq. (4)

The relationship between the $c(\theta)$ and the CHF weights C_k has exactly the same form as Eq. (6) for the frequency response of the finite impulse response (FIR) filter.

$$A(\omega) = \sum_{k=-M}^{M} a[k]e^{-jk\omega} \tag{6}$$

where $a[k]$ is the k-th coefficient of the impulse response of the filter. This relationship allows us to design rotation response by employing the FIR filter design method [12] to solve for C_k.

Once the C_k are determined, the next task is to find the CHF's $H_k(\rho)$ in order to determine the correlation filter $H(u,v)$. To improve correlation output, we select $H_k(\rho)$ that minimize the average correlation energy (ACE) of a filter while satisfying the relationship in Eq. (4). The ACE can be expressed as follows:

$$ACE = 2\pi \sum_k \left[\int_0^\infty |H_k(\rho)|^2 P_{avg}(\rho)\rho d\rho\right] \tag{7}$$

where $P_{ave}(\rho)$ is the power spectrum of the input pattern and it can be shown as:

$$P_{avg}(\rho) = \sum_{k=-\infty}^{\infty} |F_k(\rho)|^2 \tag{8}$$

where $F_k(\rho)$ is the k-th CHF of the 2-D polar FT of input pattern $f(x,y)$.

The OTCHF filter is designed to minimize ACE in Eq. (7) while satisfying the relationship in Eq. (4). Thus, the OTCHF filter $H(u,v)$ can be obtained by solving the following minimization problem.

$$\begin{aligned} &\text{Find } H_k(\rho) \text{ to minimize} \\ &\qquad \int_0^\infty |H_k(\rho)|^2 P_{ave}(\rho)\rho d\rho \\ &\text{subject to} \\ &\qquad \int_0^\infty F_k(\rho)H_k^*(\rho)\rho d\rho = C_k \end{aligned} \tag{9}$$

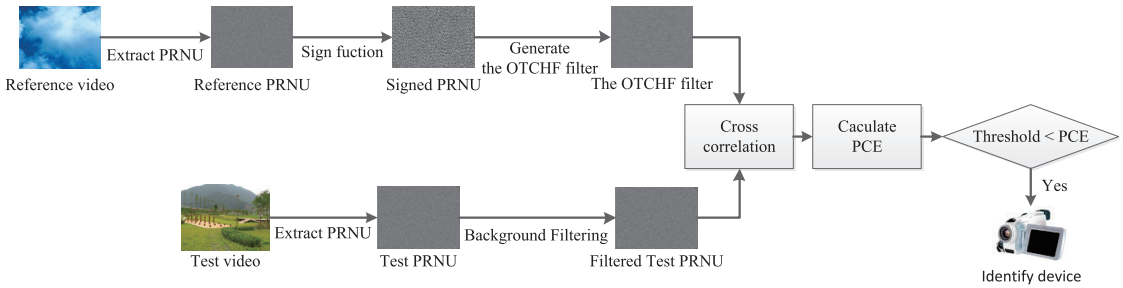

Fig. 3 Proposed identification procedure.

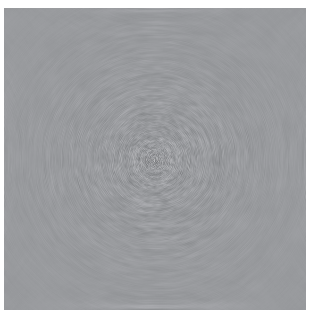

Fig. 2 OTCHF filter generated from PRNU.

Using the method of Lagrange multipliers, the solution to the minimization problem of Eq. (9) can be found to be

$$H_k(\rho) = \lambda_k{}^* \frac{F_k(\rho)}{P_{avg}(\rho)}, \quad where\ \lambda_k = \frac{C_k}{\displaystyle\int_0^\infty \frac{|F_k(\rho)|^2}{P_{avg}(\rho)} \rho d\rho}. \tag{10}$$

After we have $H_k(\rho)$, the correlation filter $H(u, v)$ can be found by applying the inverse Eq. (1) and a polar-to-cartesian coordinate transform. Figure 2 shows the OTCHF correlation filter computed from PRNU.

3. Proposed Source Device Identification Method

The previous section described how an OTCHF was designed. In this section, it is explained how the OTCHF filter is applied to camera identification.

Figure 3 depicts the overall procedure of the proposed camera identification method. First, the test PRNU and the reference PRNU are extracted from a test video and a reference video of the test camera. The PRNU model in [3] is adopted for extracting the PRNU from videos. Let us assume that we have a video clip consisting of N frames $I_1, I_2, \ldots, I_n$. The PRNU is extracted as follow:

$$PRNU = \sum_{k=1}^{N} \frac{W_k \hat{I}_k}{(\hat{I}_k)^2}\ where\ \hat{I}_k = F(I_k),\ W_k = I_k - \hat{I}_k \tag{11}$$

where F is the wavelet-based de-noising filter described in [2].

Second, the reference PRNU and the test PRNU are filtered to enhance the detection accuracy. The transform functions for generating the OTCHF filter introduce additional distortion to the PRNU, which can be a serious factor of performance degradation. To minimize the effect of distortion, we calculate the signed reference PRNU $\tilde{R}$ as follow:

$$\tilde{R} = \mathrm{sgn}(R) \tag{12}$$

where R is the reference PRNU and $sgn()$ refers to the sign function. Simultaneously, test PRNU is filtered by model 5 in [5] to remove background noises as follow:

$$\tilde{T}(i, j) = \begin{cases} e^{-0.5T(i,j)^2/\alpha^2}, & if\ 0 \le T(i,j) \\ -e^{-0.5T(i,j)^2/\alpha^2}, & \text{otherwise} \end{cases} \tag{13}$$

where $T(i, j)$ is test PRNU and $\alpha = 7$.

After filtering the PRNUs, we generate the OTCHF filter from $\tilde{R}$ which can be expressed by the filter design function f_0 as follows:

$$H = f_0(\tilde{R}, c(\theta)) \tag{14}$$

with a given rotation tolerance specification $c(\theta)$,

$$c(\theta) = \begin{cases} 1, & if\ |\theta| \le \theta_t \\ 0, & otherwise \end{cases} \tag{15}$$

where θ_t is the tolerance angle.

Because of trade-off between rotation-tolerance and discrimination of filter, the OTCHF correlation filter shows high performance when θ_t is small. In a real world scenario, attackers may rotate test videos by very small angles, which are not perceived by humans, because they do not want to expose their manipulation. Therefore, θ_t is set as 2.5° for the OTCHF design.

Finally, we measure the correlation between the OTCHF filter H and the filtered test PRNU $\tilde{T}$ as follow:

$$cc(x, y) = \sum_{m=0}^{M} \sum_{n=0}^{N} H(m, n) \cdot \tilde{T}^*(m + x, n + y) \tag{16}$$

Then, we examine the correlation output $cc(x, y)$ and decide whether a test video was taken by a test camera by detecting the presence of a pronounced peak in $cc(x, y)$. Several difference measures exist to detect peak sharpness [11]. In this paper, we calculate the peak to correlation energy (PCE) measure as follows:

$$PCE = \frac{cc(i_{peak}, j_{peak})}{\displaystyle\sum_{i,j} cc(i, j)^2} \tag{17}$$

where (i_{peak}, j_{peak}) are the peak positions in $cc(x, y)$. It is determined that the test video was taken by the test camera when the PCE value is greater than the pre-defined threshold τ_{pce}

4. Experimental Results

Experiments were conducted with ten cameras. With the videos taken by these cameras, we totally prepared 100 high quality test videos. All the videos were taken with resolution of 640×480, H.264 with 5 Mb/sec, frame rate of 30 Hz, and 30 seconds recoding time. Other conditions such as white balance, sharpness, contrast and etc., were automatically set. We extracted reference PRNU from blue-sky videos for each camera and generated OTCHF correlation filters from them.

In order to measure the performance with rotated videos, 100 videos were rotated in increments of 0.1° from −2.5° to 2.5° by bi-cubic interpolation kernel. Then, the center of the rotated videos is cropped to make 640×480 videos. The proposed method was carried out for every test video and calculated the identification rate according to each rotation factor. We also compared the proposed method with Li's method [5].

To decide the identification threshold τ_{pce}, we calculated PCE values between the OTCHF correlation filters which represented each camera and the test PRNUs from every test video. Figure 4 depicts ROC curves compiled from all the pairs with different τ_{pce}. From the results, we determined threshold τ_{pce} at which false positive rate (FPR) was 10^{-2} and measured the identification accuracy. Figure 5 shows the identification rate at FPR=10^{-2} for each rotation factor. The experimental results indicate that the proposed method is more robust to the rotation attack than Li's method.

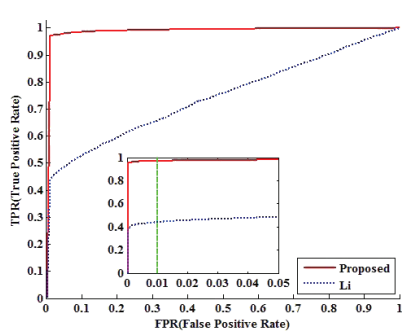

Fig. 4 ROC curves for the proposed and Li's method.

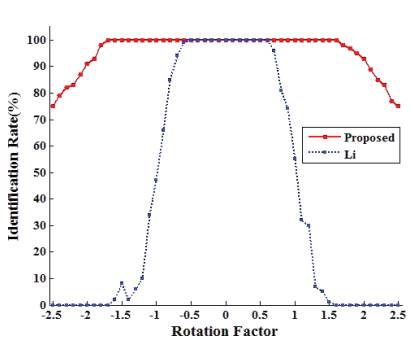

Fig. 5 Identification accuracy at FPR=10^{-2}.

5. Conclusions

In this paper, we proposed an improved PRNU-based camera identification method which performs well with rotated videos. By employing the rotation-tolerance property of the OTCHF correlation filter, the proposed method could solve the out-of-sync problem by rotation attacks. More specifically, we designed the OTCHF correlation filter from reference PRNU and applied this filter to camera identification. The experimental results demonstrated that the proposed method could detect the source camera with high accuracy for rotated videos.

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