Exploiting Power Signatures for Camera Forensics

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***Abstract*—The electric network frequency (ENF) is a signature of power distribution networks that can be captured by multimedia signals recorded near electrical activity. This has led to the emergence of multiple forensic applications based on the use of ENF signals. Examples of such applications include validating the time of recording of an ENF-containing multimedia signal or inferring the grid in which it was recorded. In this letter, we explore a novel ENF-based application that seeks to characterize the camera that has produced a given video. Inspired by recent work on exploiting flicker for pirate device identification, we investigate the use of ENF captured in a video to characterize the camera that has produced the video through a nonintrusive procedure that estimates the camera's read-out time. The proposed technique has achieved a high accuracy in estimating this discriminating parameter with a relative estimation error within 1.5%.**

***Index Terms*—Electric network frequency (ENF), read-out time, rolling shutter, video camera forensics.**

I. Introduction

The electric network frequency (ENF) is the frequency of power distribution networks. It has a nominal value of 60 Hz in North America and 50 Hz in most other parts of the world. The ENF typically fluctuates around its nominal value due to changing loads across the grid. We define the *ENF signal* as the changing value of the ENF over time. As ENF variations are often inherently captured in audio and video recordings made in areas where there is electrical activity, these traces have shown promise in recent years for a number of multimedia forensics applications. The ENF signal embedded in such media recordings can be used to time stamp the recording, locate its grid of origin, or determine whether or not it has been tampered with, among other applications [1]–[6].

In this letter, we explore a novel application of the ENF signal that is targeted at characterizing the camera that has produced an ENF-containing video. This can be particularly useful in scenarios where there is a need to verify that a suspect owns a camera that produced a suspicious video. Our focus is on the widely used cameras with complementary metal-oxide semiconductor (CMOS) image sensors that employ a *rolling shutter*. Unlike a camera employing a *global shutter* that acquires all the pixels of a video frame at the same time, a camera employing a rolling shutter acquires a video frame one row at a time. Although this sequential read-out mechanism of rolling shutter has traditionally been considered detrimental to image/video quality due to its accompanying artifacts, recent work has shown that it can be exploited with computer vision and computational photography techniques to produce interesting results [7], [8]. Recent work on ENF, for instance, has made use of the rolling shutter toward improved ENF extraction from videos [4], [9], [10].

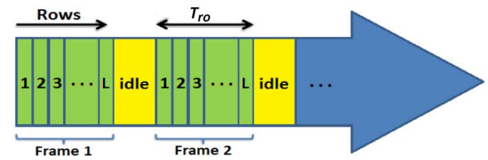

Fig. 1. Timing of rolling shutter sampling: the L rows of a frame are sequentially exposed, followed by an idle period before proceeding to the rows of the next frame.

Fig. 1 illustrates the timing for image acquisition with rolling shutter. Each row of the frame is sequentially exposed to light followed possibly by an idle period before proceeding to the next frame [9]. The amount of time during which a camera acquires the rows of a video frame, which we denote by the read-out time T_{ro} is specific to the camera and is a value that is not typically mentioned in its user manual or specifications list. In this letter, we characterize the camera that has produced an ENF-containing video by estimating its T_{ro} value.

The work discussed in this letter is inspired by recent work on flicker-based video forensics that addresses issues in the entertainment industry pertaining to movie piracy related investigations [11], [12]. The focus of that work was on pirated videos that are produced by camcording video content displayed on an LCD screen. Such pirated videos commonly exhibit an artifact called the flicker signal, which results from the interplay between the back light of the LCD screen and the recording mechanism of the video camera. In [12], this flicker signal is exploited to characterize the LCD screen and camera that have produced the pirated video, through estimating the frequency of the screen's back-light signal and the camera's read-out time T_{ro} value.

Both flicker signals and ENF signals are signatures that can be intrinsically embedded in a video due to the camera's recording mechanism, and the presence of a signal in the recording environment. For the flicker signal, the environmental signal is the back-light signal of the LCD screen while for the ENF signal, it is the electric lighting signal in the recording environment. Here, we leverage the similarities between the two signals to adapt the flicker-based approach to an ENF-based approach targeted at characterizing the camera producing the ENF-containing video. Due to the ease of detecting the nominal value of an embedded ENF signal, the ENF-based approach works in a completely nonintrusive scenario, whereas the previous flicker-based approach works in a semi-nonintrusive scenario.

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The rest of this letter is organized as follows. Section II explains our model for signal capture and the proposed approach for estimating the read-out time of the camera that has produced an ENF-containing video; Section III discusses the experimental setup and results; and Section IV summarizes this work.

II. Model and Proposed Approach

ENF traces are embedded in the visual track of video recordings through the changing intensity of electric lighting captured by the camera. The electric light intensity relates to the supplied electric current via a power law thus making its nominal frequency twice the nominal ENF value, i.e., 120 Hz in North America and 100 Hz in most other parts of the world. Following this, the electric light signal can be modeled as a sinusoid

$$x(t) = A_e \sin\left(2\pi \tilde{f}_e t + \phi\right) \tag{1}$$

where $\tilde{f}_e := f_e(t)$ represents a variable frequency, corresponding to the ENF component that fluctuates around 100/120 Hz, and A_e and ϕ are the magnitude and phase, respectively.

In what follows, we model the light intensity signal captured in a video by a camera [13]. Then, we describe our proposed approach to estimate the camera's read-out time.

A. Modeling the Captured Signal

The process in which a camera acquires a video can be seen as a two-step process. First, integration of photons happens over a duration ΔT, which refers to the camera's *shutter speed*. Second, the camera samples the resulting integration signal.

The integration phase can be modeled as a convolution of the light signal $x(t)$ with a rectangular integration window $h(t)$ whose Fourier transform can be written as $H(f) = \Delta T \text{sinc}\,(f\Delta T)$. The Fourier transform of the signal obtained is then

$$\begin{aligned} Y(f) &= X(f) \cdot H(f) && (2)\\ &= \frac{A_e}{2}\left[e^{-j\phi}\delta\left(f - \tilde{f}_e\right) + e^{j\phi}\delta\left(f + \tilde{f}_e\right)\right] \cdot H(f) && (3)\\ &= \frac{A_e \Delta T}{2}\text{sinc}\left(\tilde{f}_e \Delta T\right)\left[e^{-j\phi}\delta\left(f - \tilde{f}_e\right) + e^{j\phi}\delta(f + \tilde{f}_e)\right]. && (4) \end{aligned}$$

This allows us to write $y(t)$ as $\tilde{A}\sin(2\pi \tilde{f}_e t + \phi)$, where $\tilde{A} = \frac{A_e \Delta T}{2}\text{sinc}(\tilde{f}_e \Delta T)$.

To model the sampling phase of the camera's acquisition of the light intensity signal, we first need to define the camera's sampling rate. To begin with, we write the camera's frame rate f_c as $f_c = 1/T_c$, where T_c is the frame period. T_c includes the period of time T_{ro} required to sample the L rows of a frame and possibly an additional idle time period. Since the camera being considered in this letter employs a rolling shutter, each row is sampled at a different time, so the sampling rate that we are interested in is not f_c, but rather $f_s = 1/T_s$, where T_s is the time between subsequent row read-outs. For modeling purposes, we assume that if the camera read-out is performed continuously at a rate of f_s for the entire frame period T_c, i.e., in a case where there is no idle time, then the camera would in principle be able to read out M rows for the duration of T_c where $M \geq L$, with L being the actual number of rows in a frame. Following this, we can express the camera's sampling rate f_s as

$$f_s = \frac{1}{T_s} = \frac{M}{T_c} = \frac{L}{T_{ro}}. \tag{5}$$

In this setting, M is unknown, but L can be found by examining the video height in the video's metadata.

We denote the sampled signal by $s[n] = y(nT_s)$ for $n \in \mathbb{N}$. This can be written as

$$s[n] = \tilde{A}\sin\left(2\pi \tilde{f}_e T_s n + \phi\right) \text{ for } n \in \mathbb{N}. \tag{6}$$

The intensity value $s[n]$ is the light intensity captured by all the pixels in the nth row. To make the relation clearer, we write n as $n = kM + l$, where k and l are the frame and row indices, respectively, such that $k \in \{0, 1, 2, \ldots, F-1\}$ and $l \in \{0, 1, 2, \ldots, M-1\}$, with F being the number of frames in the video.

Replacing n by $kM + l$ in (6), and using (5), we obtain

$$\begin{aligned} s[k,l] &= \tilde{A}\sin\left(2\pi \tilde{f}_e \frac{T_c}{M} kM + 2\pi \tilde{f}_e T_s l + \phi\right) && (7)\\ &= \tilde{A}\sin\left(2\pi \frac{\tilde{f}_e}{f_c} k + 2\pi \frac{\tilde{f}_e}{f_s} l + \phi\right). && (8) \end{aligned}$$

Since a video camera's frame rate f_c typically falls in the range of 24–60 Hz, we would have $\tilde{f}_e > f_c$. To account for aliasing, we write $\tilde{f}_e$ as

$$\tilde{f}_e = \tilde{f}_a + m f_c, \text{ where } m \in \mathbb{N} \text{ and } \tilde{f}_a \in [-f_c/2, f_c/2]. \tag{9}$$

We can now write $s[k,l]$ as

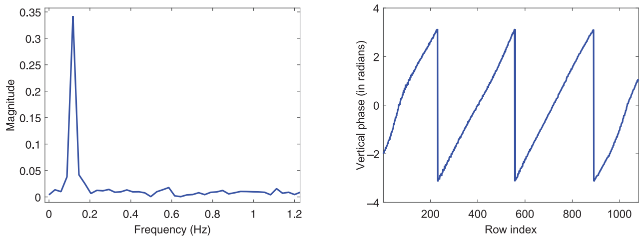
$$\begin{aligned} s[k,l] &= \tilde{A}\sin\left(2\pi \frac{\tilde{f}_a}{f_c} k + 2\pi m k + 2\pi \frac{\tilde{f}_e}{f_s} l + \phi\right) && (10)\\ &= \tilde{A}\sin\left(2\pi \frac{\tilde{f}_a}{f_c} k + 2\pi \frac{\tilde{f}_e}{f_s} l + \phi\right) && (11)\\ &= \tilde{A}\sin\left(\tilde{\omega}_a k + \tilde{\omega}_b l + \phi\right) && (12) \end{aligned}$$

where $\tilde{\omega}_a = 2\pi \tilde{f}_a / f_c$ is expressed in *radians/frame* and $\tilde{\omega}_b = 2\pi \tilde{f}_e / f_s$ is expressed in *radians/row*.

B. Proposed Approach

In this section, we first describe the *vertical phase method*, which was inspired by the related flicker forensics work [12] and on which we based our proposed approach. We then explain how we adapt the *vertical phase method* to our ENF-based approach in a practical setting.

1) Vertical Phase Method: This method examines the evolution of the embedded intensity signal, $s[k,l]$, over frames, and computes the vertical radial frequency $\tilde{\omega}_b$ to aid the estimation of the read-out time T_{ro}. By exploiting $\tilde{\omega}_b$'s relation to the delay between ENF traces in adjacent rows, we can estimate it through analyzing the phase shift in the discrete-time Fourier transforms (DTFTs) of the row intensity signals.



(a) Fourier transform of s_{l^*} showing peak close to the expected $\tilde{f}_a$

(b) Linear vertical phase

Fig. 2. Results of applying the *vertical phase method* on a video taken by the back camera of an iPhone 5.

For simplicity, we first assume that the time-varying parameters involved, namely, $\tilde{\omega}_a, \tilde{\omega}_b, \tilde{f}_a$, and $\tilde{f}_e$, are all constant at their respective nominal values. We will relax this assumption in Section II-B(2).

The first step is obtaining an estimate for the aliased frequency $\tilde{\omega}_a$. To do that, we examine the following modification of (12):

$$s_{l^*}[k] = \tilde{A} \sin\left(\tilde{\omega}_a k + \tilde{\omega}_b l^* + \phi\right). \tag{13}$$

Here, we fix the row index l to a certain value l^*, and the resulting signal $s_{l^*}[k]$ as a function of the frame index k is a sinusoid of frequency $\tilde{\omega}_a$. An estimate of $\tilde{\omega}_a$ can then be obtained by finding the frequency that shows a peak in the Fourier transform of $s_{l^*}[k]$. We can equivalently find an estimate of $\tilde{f}_a$ using $\tilde{f}_a = \tilde{\omega}_a f_c / 2\pi$ and the known frame rate f_c. An example can be seen in Fig. 2(a), where a peak of the Fourier transform is visible close to the expected $\tilde{f}_a$.

The next step is to obtain an estimate of $\tilde{\omega}_b$. To do that, we compute the value of the DTFT of $s_l[k]$ at $\tilde{\omega} = \tilde{\omega}_a$ for each case of $l \in \{0, 1, \ldots, L-1\}$. We compile the values into a vector of size L, resulting in $S_{\tilde{\omega}_a}[l]$ that we denote as the *vertical Fourier transform*. The phase component $\Phi_{\tilde{\omega}_a}[l]$ of $S_{\tilde{\omega}_a}[l]$ can be written as

$$\Phi_{\tilde{\omega}_a}[l] = \tilde{\omega}_b l + \phi. \tag{14}$$

An example of this *vertical phase* can be seen in Fig. 2(b), wrapped between $[-\pi, \pi]$. After *unwrapping* this vertical phase, $\tilde{\omega}_b$ can be estimated from the slope using linear regression.

Now that we have an estimate of $\tilde{\omega}_b$, we can compute the T_{ro} estimate. Examining the definition of $\tilde{\omega}_b$, and using (5), we can write it as

$$\tilde{\omega}_b = 2\pi \cdot \frac{\tilde{f}_e}{f_s} = 2\pi \cdot \frac{\tilde{f}_e}{L/T_{ro}}. \tag{15}$$

Thus, we can use the known values of the frame height and the nominal ENF value to estimate the read-out time T_{ro} via

$$T_{ro} = \frac{L \cdot \tilde{\omega}_b}{2\pi \tilde{f}_e}. \tag{16}$$

2) Adapting to a Practical Setting: We now discuss how to modify the above method to obtain the T_{ro} value from the embedded ENF in a practical setting. We first need to account for the time-varying nature of the parameters that were assumed constant in the previous discussion. We also need to account for the fact that the embedded ENF traces may not always be strong enough around the nominal 100/120 Hz value. In practice, it is not uncommon for the ENF traces to be more strongly captured at higher harmonics of the nominal frequency than at the nominal value [14], [15].

Algorithm 1. Proposed approach to compute T_{ro} estimate

1: Pre-process the video for analysis.
2: Find if the nominal frequency $\bar{f}_e$ is 100 or 120 Hz.
3: Assign the origin frequency $f_o := k\bar{f}_e$, where $k := 1$.
4: Compute the aliased frequency of f_o as: $f_{a,o} = f_o - m f_c$, such that $m \in \mathbb{N}$ and $f_{a,o} \in [-f_c/2, f_c/2]$.
5: Find the frequency in $f_{a,o}$'s vicinity with the most linear vertical phase, and estimate the corresponding slope $\hat{\omega}_b$.
6: **if** the vertical phase is sufficiently linear,
7: Compute T_{ro} as: $T_{ro} = (L \cdot \hat{\omega}_b) \,/\, \left(2\pi k \bar{f}_e\right)$.
8: **else**
9: Assign $f_o := k\bar{f}_e$, where $k := k+1$.
10: Go to Line 4.

The steps of our proposed approach are outlined in Algorithm 1. The first step is to prepare the ENF-containing video for analysis. The preprocessing operations involved here can vary depending on the video at hand, with the goal of making the embedded ENF detectable with high signal-to-noise ratio. A number of these enhancement operations have been discussed in [10]. Examples of such operations include identifying static regions in the video that are more favorable for ENF extraction, compensating for camera motion, and compensating for brightness changes that are caused by a camera's automatic brightness control mechanism. After preprocessing, for each frame of the video, we obtain a 1-D vector of size L, a *frame signal*, where the the lth entry corresponds to the contents of the frame's lth row.

Next, we must ascertain whether the nominal ENF value, $\bar{f}_e$, is 100 or 120 Hz. This can be done by examining the time–frequency content in the recorded video. To do so, we connect the frame signals from consecutive frames and compute the Fourier transform of the resulting signal. We use the *nominal row sampling rate*, defined as the product of the video's frame rate f_c and the frame height L, as a unit of reference corresponding to the Fourier transform's frequency axis. Plotting the Fourier transform would then reveal peaks at the frequency values of $\tilde{f}_e$ shifted by multiples of f_c [9]. If these peaks appear close to $120 + n \cdot f_c$, then $\bar{f}_e = 120\,\text{Hz}$, and if they appear close to $100 + n \cdot f_c$, then $\bar{f}_e = 100\,\text{Hz}\,(n \in \mathbb{N})$.

Assigning $f_o := \bar{f}_e$ and via Line 4 of Algorithm 1, we compute the aliased frequency $f_{a,o}$ where we expect to find the ENF traces. If the ENF values were constant at the nominal value, we would proceed to compute the vertical phase at $f_{a,o}$ and the corresponding slope. As the time-varying ENF is likely not to be at its nominal value during the recording of the video, the corresponding aliased frequency might not lie at the calculated $f_{a,o}$. To account for this, we sample frequencies in the vicinity of $f_{a,o}$ and compute their corresponding vertical phases. Among the

TABLE I
CAMERAS USED IN OUR EXPERIMENTS

Camera ID	Model	L	T_{ro} (ms)
1	Sony Cybershot DSC–RX 100 II	1080	13.4
2	Sony Handycam HDR–TG1	1080	14.6
3	Canon SX230–HS	240	18.2
4	iPhone 5 front camera	720	22.9
5	iPhone 5 back camera	1080	27.4

candidates, we select the most linear vertical phase, where linearity is assessed based on the root-mean-squared (RMS) error of the linear regression.

Ideally, the estimated slope of the vertical phase can reveal the read-out time using (16). However, if the vertical phase is not linear enough and the regression RMS error is not small enough, the final estimate will be incorrect. We have empirically found that a threshold of 0.04 for the regression RMS error is a good cut-off value to avoid obtaining erroneous estimates. This may happen when the ENF is not strongly captured at the nominal value. In such a case, the ENF, if present, may be more reliably captured at higher frequencies than at the nominal value, so we assign f_o to be the next harmonic of the $\bar{f}_e$ and repeat the procedure.

If a low RMS error cannot be achieved for several iterations, it may become necessary to improve the preprocessing operations [10].

III. Experiment and Results

In this section, we describe the experiment carried out to test the proposed approach and discuss the results obtained.

A. Experimental Setup

We have recorded short videos (30–75 s long each) using five different cameras in environments where there is electric lighting in Maryland, USA. The aim of the experiment is to analyze each of the videos using the proposed approach of Section II-B and estimate the read-out time T_{ro} of the video's camera.

In order to evaluate the accuracy of our ENF-based T_{ro} estimates, we need to compute ground-truth values for the T_{ro} values of the cameras at hand. We have employed a protocol described in [12] for this purpose. We build a photodiode equipped circuit that takes as an input a light signal and records it as a digital signal. We use the circuit to record the back-light signal of an LCD screen, and then analyze the Fourier transform of the recorded digital signal to estimate the screen's back-light frequency f_{bl}. Afterward, using a video camera that we wish to characterize, we take a short video, of about one minute long, by camcording a uniform gray screen displayed on the LCD screen with the now known f_{bl}. In this controlled setting, the recorded video will exhibit a strong flicker signal. Using the *vertical phase method* of Section II-B(1) and replacing $\bar{f}_e$ by the obtained f_{bl}, we can obtain a confident estimate for the camera's T_{ro} value and use it as ground truth for subsequent experimental evaluations.

We have carried out this protocol using two LCD screens on the five cameras at our disposal. Table I shows the full details for the cameras.

TABLE II
ESTIMATED T_{ro} VALUES OF CONSIDERED VIDEOS USING OUR PROPOSED APPROACH

Camera ID	1	2	3	4	5
Expected T_{ro} (ms)	13.4	14.6	18.2	22.9	27.4
Estimated T_{ro} (ms)	13.60	14.75	18.41	23.13	27.63
Relative error (%)	1.5	1.0	1.2	1.0	0.8

B. Results and Discussions

We have applied the proposed approach of Section II-B(2) on the videos taken by the five cameras in Table I. For the videos of Cameras 1 and 2, we have found good T_{ro} estimates based on the ENF traces of the second harmonic, while for Cameras 3–5, we have found good T_{ro} estimates based on the ENF traces of the base nominal frequency.

Table II shows the results obtained for the five videos. We can see that we have obtained excellent T_{ro} estimates for all the cases, with the relative error being within 1.5%.

We have clearly benefited from having short videos in this experiment, as the U.S. ENF generally remains well controlled and does not vary much within such a short time window. In the case where longer videos are to be analyzed, it would be advisable to divide the videos into shorter segments and analyze each separately so as not to be affected negatively by the changing ENF value over time.

IV. Conclusion and Future Work

In this letter, we have adapted an approach in flicker-based forensics for pirate screen and/or camera characterization to an ENF-based forensic application, whereby we are able to analyze an ENF-containing video to characterize the camera that has produced the video. This is done by estimating the camera's read-out time, or the time needed to read one frame, which is typically less than the frame period for the commonly used cameras equipped with rolling shutter. We have tested our proposed nonintrusive approach on short ENF-containing videos taken using five different cameras, where we have seen high performance in estimating read-out times.

This work shows the potential for the ENF captured in a video to characterize the camera that has produced the video. It can provide corroborating evidence in cases where a video is linked to a suspect owning a certain camera. In future work, we plan to examine a wider range of cameras to investigate the variability in read-out time values and thus better understand the broad applicability and performance of this approach. We also plan to investigate further video camera characteristics that can be extracted based on analyzing the captured ENF.

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