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PRNU Estimation based on Weighted Averaging for Source Smartphone Video Identification

Ashref Lawgaly[1], Fouad Khelifi[1], Ahmed Bouridane[2], Somaya Al-Maadeed[3], Younes Akbari[3]

[1]Department of Computer and Information Sciences, Northumbria University, Newcastle upon Tyne, UK.
[2]Department of Computer Engineering, University of Sharjah, United Arab Emirates.
[3]Department of Computer Science and Engineering, Qatar University, Doha, Qatar.

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Abstract*— Photo response non-uniformity (PRNU) noise is a sensor pattern noise characterizing imperfections in the imaging device. The PRNU is a unique noise for each sensor device, and it has been generally utilized in the literature for source camera identification and image authentication. In video forensics, the traditional approach estimates the PRNU by averaging a set of residual signals obtained from multiple video frames. However, due to lossy compression and other non-unique content-dependent noise components that interfere with the video data, constant averaging does not take into account the intensity of these undesirable noise components which are content-dependent. Different from the traditional approach, we propose a video PRNU estimation method based on weighted averaging. The noise residual is first extracted for each single video. Then, the estimated noise residuals are fed into a weighted averaging method to optimize PRNU estimation. Experimental results on two video datasets captured by various smartphone devices have shown a significant gain obtained with the proposed approach over the conventional state-of-the-art one.

Keywords: PRNU, Source Smartphone Identification, Video Forensics, weighted averaging.

I. INTRODUCTION

Nowadays, it's become widely common to use portable devices in everyday life because of their unquestionable benefits. A good example of such device is smartphone, which includes a camera for taking high quality images and recording high-definition videos. As a result, millions of videos are regularly shared daily through social media platforms under the assumption that the data and users are genuine. This may however raise major concerns especially in cases of copyright infringements or where multimedia contents are sensitive and incriminating individuals. Identifying the source of digital smartphone videos could therefore be an effective way to address such concerns in the field of video forensics. This paper is concerned with efficient estimation of the Photo Response Non-Uniformity (PRNU) noise for videos recorded by a smartphone. The PRNU noise can be considered as a sensor pattern noise that can characterises the imaging device and it has been generally used in the literature for image authentication and source camera identification[1]. The PRNU noise is caused by the sensitivity of pixels to light which is produced due to the imperfections and non-homogeneity of silicon wafers during the manufacture of camera sensor. The sufficient data that PRNU carries in terms of frequency content makes it unique and consequently suitable for identifying the source smartphone video and detecting video forgeries. Nevertheless, the PRNU estimation method may be faced with the presence of video/image-dependent information as well as other non-unique noise components. A basic model of the sensor output could be expressed as shown in (1), where J^0 denotes to the original video frame, J^0K is the PRNU term and Θ a random noise factor. PRNU is a multiplicative noise and is a weak signal of the same dimensions as the output of the video frame, denoted in this work by $K \in \mathcal{R}^{\mathcal{W}\times\mathcal{V}}$, where $\mathcal{W}\times\mathcal{V}$ represent the dimension of the sensor [2],[3].

$$J = J^0 + J^0K + \Theta \tag{1}$$

Image forensics is concerned with image integrity verification, authentication, and Source Camera Identification (SCI) via image processing and analysis [1]. The first technique to identify the source of digital images using the PRNU was suggested by [2]. In this technique, the residual signal R_i is calculated by denoising an image J_i using wavelet-based de-noising filter[4]. Next the residual signal is obtained from an image J_i as $R_i = J_i - F(J_i)$ where the $F(J_i)$ is the de-denoised image. Finally, the K, is computed as shown in (2) by averaging N residual signals, where N refers to the number of images used to estimate the PRNU. Once K is estimated, the normal correlation is used as a similarity measure as shown in (3) where $\bar{K}, \bar{R}$ represents the means of K, R respectively.

$$K = \frac{\sum_{i=1}^{N} R_i}{N} \tag{2}$$

$$P(K,R) = \frac{\sum_m \sum_n (K_{mn} - \bar{K}).(R_{mn} - \bar{R})}{\sqrt{(\sum_m \sum_n (K_{mn} - \bar{K})^2)\,(\sum_m \sum_n (R_{mn} - \bar{R})^2)}} \tag{3}$$

In [3], PRNU was estimated based on the Maximum Likelihood Estimator (MLE). Then, the peak-to-correlation energy (PCE) is used to measure similarity. In [5], an improved locally adaptive DCT Filter(LADCT) was developed in [6] to estimate PRNU efficiently by taking into account the varying strength of PRNU in local image regions. Although several methods based on PRNU estimation were developed for digital images such as [2, 3, 5-12], less research has been devoted to the forensic analysis of digital videos. In [13] the authors extended their PRNU estimation method [2] from digital images to videos and demonstrated that the PRNU can still be used to link a video to its source camcorder efficiently. In this technique, the PRNU was estimated from both (training and query) videos using MLE. In [14] several texture measures obtained from the Grey Level Cooccurrence Matrix (GLCM) was used, in order to select suitable training video frames (i.e., non-textured frames) for SCI. Chuang et al. [15] and Goljan et al. [16] evaluated the video compression impact on PRUN estimation in the compressed domain. Also, [17] is another work that also considers the effect of video compression, but it also attempts to attenuate the high-frequency details that may be contained in video frames to improve PRNU estimation. In [18] confidence weight PRNU method based on image gradient magnitudes is proposed to reduce the impact of video content and improve the PRNU estimation. The authors in [15] showed that PRNU estimation from I-frames is more reliable than B-frames and P-frames in the compressed domain. In [19], a PRNU-based source camera identification technique using out-of-camera stabilised videos were proposed in the compressed domain. The technique uses 50 I-frames from each video to estimate the PRNU. The authors In [20] studied the effect of camera rolling with various degrees on PRNU estimation. In [21], the video frames were resized to 512×512 prior to PRNU estimation from the green channel which is said to be the noisiest channel among in RGB videos. In [22] and in an attempt to boost the performance of PRNU estimation, a hybrid approach that uses both videos and still images was proposed. In this method, the PRNUs are estimated from still images obtained by the source device, while the query PRNU is estimated from the video and subsequently linked with the reference to verify the possible match. In [23] , the minimum average correlation energy (MACE) filter [24] was applied to reduce the impact of heavily compressed in low-resolution videos. In this technique, the reference PRNU was extracted from a number of videos, and then the MACE filter was applied for the reference PRNU to reduce the impact of noises on normalized cross-correlation (NCC). In [25] ,the authors analysed some factors such as resolution, length of the video, and compression, which could influence a decrease of the PRNU's correlation value in videos. While there were several research works attempting to enhance the PRNU estimation for source smartphone video identification, an effective approach that takes into consideration the frame content is still lacking. In this paper, noise residuals estimated from the available videos are fed into a weighted averaging method in order to take into account the various intensities of the undesirable and content-based patterns that are present in each video. This paper is structured as follows; section 2 describes the proposed technique. Experimental results are provided in section 3. A conclusion is drawn in section 4.

II. PROPOSED PRNU ESTIMATION APPROACH

The logic behind the proposed method is that the PRNU noise can be significantly affected in smartphone videos due to the lossy compression nature in which digital videos are stored, distortions that mainly occur in the textured and edged regions. Fig. 1 gives a high-level representation of the proposed approach for source smartphone video identification. In phase 1, the noise residual of the video (nrv) is estimated by using frames in a single video. In this phase, frames are extracted from a video and converted to grey level, after that the residual signal is obtained for each frame, next the noise residual of the video is estimated by averaging all residual signals in that video. Because compression artifacts are highly dependent on video contents, a simple averaging cannot remove efficiently such effect from the PRNU. Therefore, the variance of the undesirable noise that interferes with the estimated noise residual could well differ from a video to another. In this paper, we borrow the Weighted Averaging (WA) method from [26] to address this problem with the aim to enhance PRNU estimation from a theoretical perspective since WA is optimal in terms of the mean squared error. In phase 2, the PRNU is obtained via WA. Finally, each smartphone PRNU is stored in a database to be used later for identification. It is worth mentioning that WA is used only at the estimation stage. At the matching stage, the noise residual of the query video is compared with the estimated and stored PRNUs in the database using the correlation measure. After that the closest PRNU is said to correspond to the smartphone which has been used to record the video. The traditional approach for PRNU estimation uses the concept of constant averaging as in [2],[8],[9], [20] and [21]. In the rest of the paper, such traditional approaches are referred to as "Basic Video PRNU". With the aim to reduce the effect of undesirable noise components and lossy compression on PRNU estimation, this work adopts a new weighted averaging method to enhance source smartphone identification with more accurate PRNU estimation. The proposed approach is named the "Video WA PRNU". Let x_i (i=*1,2,…,N*) be N noisy observations of a signal s. The noise n_i is assumed with a zero mean and a variance denoted by σ_i^2.

$$\boldsymbol{x_i(j) = s(j) + n_i(j)\ , i = 1, \dots, N; j = 1, \dots, L} \qquad (4)$$

The traditional approach to estimate s consists of averaging the observations. As described in Eq. (5), this approach averages the observations. This is called constant averaging in the sense that every single observation is equally multiplied by a constant 1/N. In theory, the constant averaging method is optimal only if the noise variance is constant in all observations [26]. The WA method relies on the theory of unknown signal estimation from a number of noisy observations [27]. If the noise variance varies from one observation to another, the WA method can offer the best estimation to the real signal in terms of the mean squared error [26] [27].

$$\hat{s}(j) = \frac{1}{N}\sum_{i=1}^{N} x_i(j) \qquad (5)$$

The WA can be calculated as:

$$\hat{s}(j) = \sum_{i=1}^{N} w_i x_i(j) \qquad (6)$$

w_i refers to a weight for the i^{th} observation which can be calculated by Eq. (7). The estimated noise variance can be obtained as in (8).

$$w_i = \frac{1}{\sigma_i^2}\left(\sum_{m=1}^{N}\frac{1}{\sigma_m^2}\right)^{-1}, i = 1,..,N \qquad (7)$$

$$\hat{\sigma}_i^2 = \frac{\sum_{j=1}^{L}(\hat{n}_i(j) - \bar{n}_i)^2}{L}\ ,\ j = 1, \dots, L \qquad (8)$$

It is worth mentioning that the weights depend on the variance of undesirable noise in each observation. As this is usually not available in practical scenarios, an estimated version of the noise variance is used instead. This is given by Eq. (9),

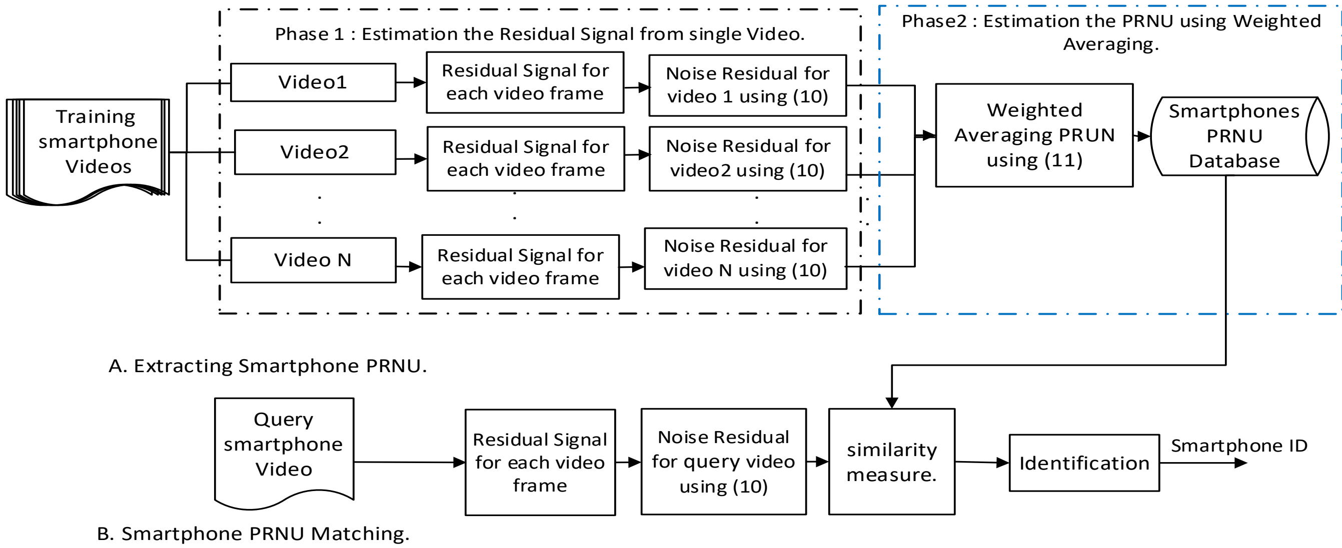

Fig 1. High-level of proposed for source smartphone video identification system.

where $\bar{x}$ refers to the average signal of the observations [26].

$$\hat{n}_i(j) = x_i(j) - \bar{x}(j) \tag{9}$$

Fig 2 shows the PRNU estimation for source smartphone video identification. First the frames are extract from a single video and de-noised using wavelet denoising filter [4]. Next, the residual signal is gained from each frame as $R_i = J_i - F(J_i)$. As shown in Eq. (10), the noise residual of a single video (nrv_t) is obtained by averaging residual signals estimated from individual frames, where M and N represents to the number of available frames in each video and number of available videos respectively. After that, each nrv is converted to 1D signal, and the optimal weights for each observation are obtained as shown in (7). Finally, the smartphone PRNU is obtained via WA as in (11).

$$nrv_t = \frac{\sum_{i=1}^{M} R_i}{M} \qquad ,t = 1..N \tag{10}$$

$$PRNU = \sum_{i=1}^{N} w_i \,.\, nrv_i \tag{11}$$

III. EXPERIMENTAL RESULTS

In this section, the evaluation is conducted using two different datasets: our smartphone dataset and the Video-ACID dataset [28]. Tables 1 and 2 show a list of 26 smartphones used in this paper (8 smartphones from our dataset and 18 smartphones are downloaded from Video-ACID [28]). It is worth mentioning that this work contains videos from 11 different brands, 23 different phone models and some of these videos are recorded by the same make and brand device, for instance iPhone 8 Plus, Motorola E4, and Sony Xperia L1, letter A and B are used to differentiate between them (see Table 1 and 2). The PRNU is estimated from 50 videos recorded by the same smartphone, while the remaining videos are used in the testing stage. The PRNU estimation and testing stages have been performed by considering cropped blocks from the frame with size of 512 × 512. The blocks are cropped from the center of the full-size frame without affecting their content. In this work, the proposed WA PRNU estimation method is compared to the traditional estimation approach on smartphone videos. Here, it is meant by the traditional approach the techniques that use the concept of constant averaging of the noise residuals in order to estimate the PRNU as in[2],[8],[9], [20] and [21]. For fair comparison, the well-known wavelet-based Wiener filter [4] has been used to de-noise each video frame in both approaches (the traditional and the proposed). In the first set of experiments, the changes in the correlation coefficient values that describe the similarity between two PRNUs of the same smartphones for each approach (the proposed video WA PRNU vs Basic Video PRNU) were examined. The correlation coefficient for each approach is calculated as shown in (3) among the PRNU estimated from query videos and the actual PRNU estimated from reference videos. Next, for each approach, the average correlation coefficient values for all testing videos were calculated for each smartphone. Fig 3 shows the mean of correlation values between every video and its PRNU. The results show that the proposed video WA PRNU estimation method has higher values of correlation coefficients compared to the traditional approach for most of the smartphones. The main goal of source smartphone video identification is to identify the smartphone used to record the video. Here, it is supposed that the video is recorded by one of the existing smartphones. Consequently, a query video is assigned to a specific smartphone if the corresponding PRNU provides the highest correlation values. The results of the false negative rate (FNR) and false positive rate (FPR) on Video-ACID [28] are depicted in Table3 and Table 4. Clear enhancements are shown on the majority of tested smartphones, for instance the FNR has been decreased from 40.6% to 31.9%, 4.6% to 1.3. %, and from 95.2% to 13.4 %.

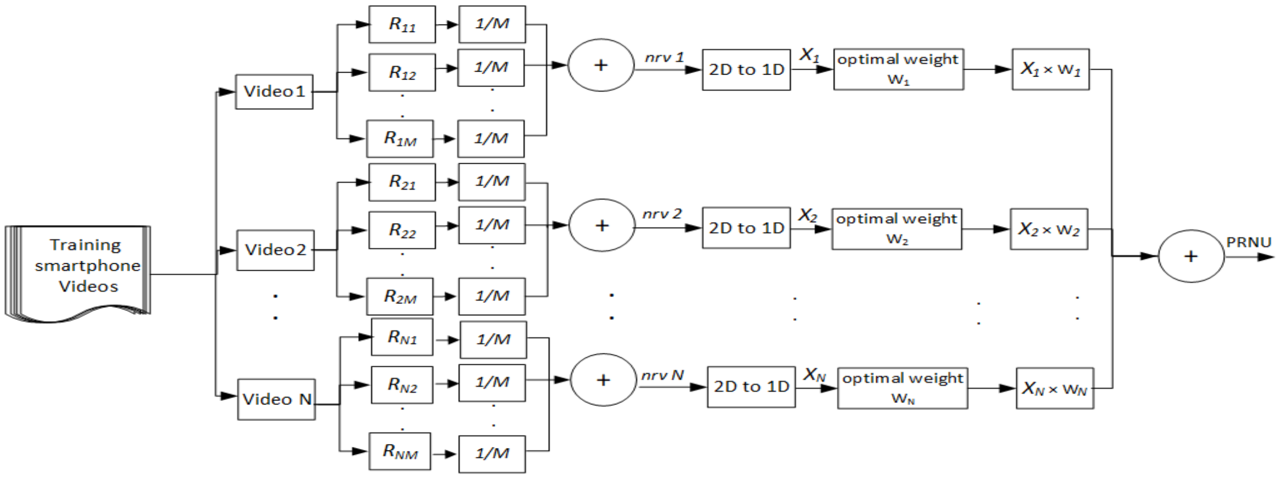

Fig 2. proposed PRNU estimation for source smartphone video identification.

Table 1: Digital Smartphones in (Video-ACID) [28].

Smartphone name	Symbol	No of videos
Apple iPhone 8 plus	M1	223
Asus Zenfone3 Laser	M2	234
Google Pixel 2	M3	187
Huawei Honor	M4	238
Huawei Mate SE	M5	257
Kodak Ektra	M6	239
LG Q6	M7	260
LG X Charge	M8	234
Motorola E4(A)	M9	251
Motorola E4(B)	M10	227
Motorola G5 Plus	M11	439
Nokia 6.1	M12	234
Samsung Galaxy S3	M13	230
Samsung Galaxy S5	M14	257
Samsung GalaxyS7	M15	206
Samsung_J5 6	M16	203
Sony Xperia L1 (A)	M17	233
Sony Xperia L1 (B)	M18	237

Table 2: Digital Smartphones in Our Dataset.

Smartphone name	Symbol	No of videos
Huawei Y7 Prime 2019	M19	300
iPhone 8 Plus	M20	216
iPhone XS Max	M21	300
Nokia 5.4	M22	300
Nokia 7.1	M23	300
Samsung A50	M24	300
Xiaomi Remi Node 8	M25	300
Xiaomi Remi Node 9 Pro	M26	300

Furthermore, another example of a clear enhancement can be seen in Table 3 especially in smartphone M02, M07 and M08. Table 4 illustrates the FPR for each smartphone using both approaches. As can be seen, a significant enhancement is obtained using the proposed approach in twelve smartphones out of eighteen. Additionally, using the proposed video WA PRNU the FPR for M01 and M10 has been reduced from 5.1% to 1.6% and from 13% to 0.8%, respectively.

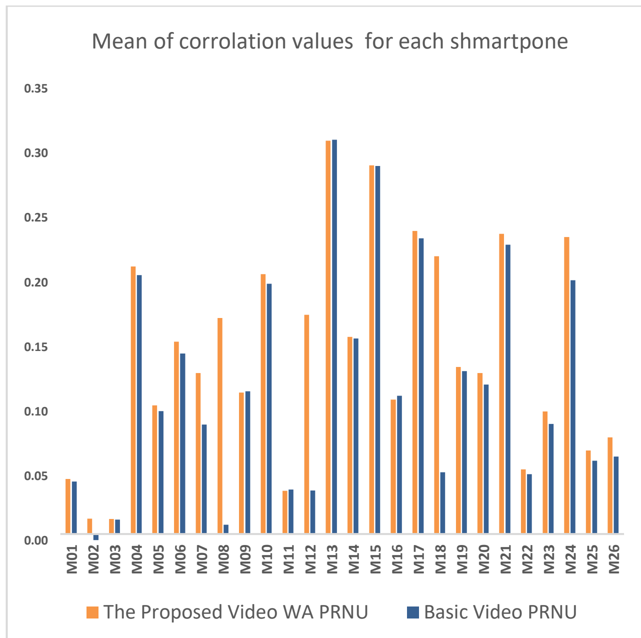

Fig 3. Mean correlation values for each smartphone suing the basic video PRNU and the proposed approach.

The results of FNR and FPR on our dataset are shown in Table 5 and Table 6. As shown, a smaller improvement has been achieved on our dataset by using the proposed approach. For instance, the FPR has been reduced slightly in M19, M21, M23, and M26, while a better enhancement is shown in M25 where the FPR is decreased from 48% to 26.8%. Also, another small improvement in FPR can be seen in Table 6. Although the proposed approach does not always give an improvement for each smartphone in both datasets, the overall FNR and FPR of the proposed Video WA PRNU approach exceeds that with the traditional Basic Video PRNU. Considerable enhancements are achieved on Video-ACID dataset, where the decrease in overall FNR and overall FPR reaches 19% and 1% less respectively (see Table 3 and 4). Less significant but noticeable improvements have been achieved on our dataset where the overall FNR and overall FPR have been decrease from 43.4% to 40.9% and from 6.4% to 6% respectively (see Table 5 and 6).

Table 3. FNR (%) for each smartphone (Video-ACID) using the traditional Basic Video PRNU and proposed Video WA PRNU.

Methods	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10	M11	M12	M13	M14	M15	M16	M17	M18	overall FNR
Basic Video PRNU	9.8	100	98.5	2.1	40.6	3.7	87.1	95.1	0.0	5.1	61.4	90.8	17.2	27.1	0.6	4.6	4.9	95.2	41.3
Video WA PRNU	12.7	91.8	94.2	2.1	31.9	3.7	1.4	4.3	0.5	9.6	63.2	5.4	23.3	30.4	0.6	1.3	12.6	13.4	22.4

Table 4. FPR (%) for each smartphone (Video-ACID) using the traditional Basic Video PRNU and proposed Video WA PRNU.

Methods	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10	M11	M12	M13	M14	M15	M16	M17	M18	overall FPR
Basic Video PRNU	5.1	0.1	0.2	8.8	2.7	0.2	2.5	0.8	4.5	13.0	0.2	0.8	0.1	0.2	0.6	0.2	4.7	0.2	2.5
Video WA PRNU	1.6	1.9	0.4	6.1	1.1	0.1	10.0	0.4	0.2	0.8	0.1	0.3	0.0	0.1	0.8	0.4	0.0	0.8	1.4

Table5. FNR (%) for each smartphone (Our dataset) using the traditional Basic Video PRNU and proposed Video WA PRNU.

Methods	M19	M20	M21	M22	M23	M24	M25	M26	overall FNR
Basic Video PRNU	17.6	22.3	2.8	87.6	77.6	3.6	48.0	87.6	43.4
Video WA PRNU	17.2	30.1	2.4	87.6	76.8	2.4	26.8	84.0	40.9

Table 6. FPR (%) for each smartphone (Our dataset) using the traditional Basic Video PRNU and proposed Video WA PRNU.

Method	M19	M20	M21	M22	M23	M24	M25	M26	overall FPR
Basic Video PRNU	0.5	0.5	1.0	0.3	3.9	20.2	23.0	1.5	6.4
Video WA PRNU	0.5	0.4	0.8	0.4	3.0	17.4	23.7	1.6	6.0

IV. CONCLUSION

In this paper, an effective video PRNU estimation approach for source smartphone video identification has been proposed. The traditional approach uses the concept of constant averaging of the noise residuals to estimate the PRNU. The residual signals are viewed as noisy observations of the PRUN, which can contain some of non-unique noise components. Also, because compression artifacts are highly dependent on video contents; a simple averaging cannot remove efficiently such effect from the PRNU. In this work, the noise residual is first obtained for each single video. Next, the estimated noise residuals are fed into a weighted averaging method to enhance the smartphone PRNU estimation. An experimental evaluation using two different smartphone video datasets has shown the superiority of the proposed Video WA PRNU over the traditional PRNU estimation approach.

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