Sensor Pattern Noise Estimation using Non-textured Video Frames For Efficient Source Smartphone Identification and Verification

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***Abstract*— Photo response non-uniformity (PRNU) noise is a sensor pattern noise characterizing the imaging device. It has been broadly used in the literature for image authentication and source camera identification. The abundant information that the PRNU carries in terms of the frequency content makes it unique, and therefore suitable for identifying the source camera and detecting forgeries in digital images. However, PRNU estimation from smartphone videos is a challenging process due to the presence of frame-dependent information (very dark/very textured), as well as other non-unique noise components and distortions due to lossy compression. In this paper, we propose an approach that considers only the non-textured frames in estimating the PRNU because its estimation in highly textured images has been proven to be inaccurate in image forensics. Furthermore, lossy compression distortions tend to affect mainly the textured and high activity regions and consequently weakens the presence of the PRNU in such areas. The proposed technique uses a number of texture measures obtained from the Grey Level Cooccurrence Matrix (GLCM) prior to an unsupervised learning process that splits the feature space through training video frames into two different sub-spaces, i.e., the textured space and the non-textured space. Non-textured video frames are filtered out and used for estimating the PRNU. Experimental results on a public video dataset captured by various smartphone devices have shown a significant gain obtained with the proposed approach over the conventional state-of-the-art approach.**

Keywords- Photo response non-uniformity noise; source smartphone identification; digital image forensics; texture analysis; Grey Level Co-occurrence Matrix (GLCM).

I. INTRODUCTION

Over the last decade, many businesses, organizations and individuals utilize digital image and video devices in everyday life due to their undeniable advantages. A prime example of such device is smartphone, which incorporates a camera for taking good quality images /videos. As a result, videos that were recorded by a smartphone represent a reliable means for testifying incidents and providing legally acceptable evidence in courtroom. Nevertheless, videos can easily be changed using a low-cost editing software, which requires little work or knowledge. Therefore, with the intention of increasing the trustworthiness of digital videos, the process of authentication and copyright protection should be conducted. The field of image forensics is concerned with image authentication, integrity verification and Source Camera Identification (SCI) by processing digital images [1]. On the other hand, video forensics is concerned with video recorder identification and video authentication using digital videos. During the last decade, a significant number of attempts to extract features which characterize the camera device using the Photo Response Non-Uniformity noise obtained from digital images (PRNU) [2-19]. It is noteworthy that the PRNU characterise imperfections caused by the manufacturing process due to the lack of homogeneity of the silicon area in the imaging sensor [2]. The noise due to sensor imperfections is a weak signal of the same dimensions as the output image indicated here by $K \in \mathcal{R}^{\mathcal{W}\times\mathcal{V}}$, where $\mathcal{W}\times\mathcal{V}$ represent the dimension of the sensor. Even though the sensor can be different from one device to another, the final digital image output can be expressed as [3],[4].

$$J = J^0 + J^0K + \Theta \qquad (1)$$

Where J^0 refers to the original input multimedia file, J^0K represents the PRNU term and Θ is a random noise factor. In the literature, there has been an increasing body of research devoted to image source camera identification using the PRNU. Lukas et al. [3], proposed a system to estimate the PRNU-pattern, the residual signal r_i is obtained by denoising an image J_i using wavelet-based de-noising filter. 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. The PRNU, K, is the result of averaging N of the residual signal, where N refer to refers to the number of images used to estimate the PRNU. In [4], PRNU estimation technique based on Maximum Likelihood Estimator (MLE) for SCI is provided. In this algorithm, the K is given by:

$$K = \frac{\sum_{i=1}^{N} r_i J_i}{\sum_{i=1}^{N} (J_i)^2} \qquad (2)$$

In [5], the authors proposed an improved locally adaptive DCT Filter followed by a weighted averaging to exploit the content of images carrying the PRNU efficiently. While several of forensic techniques were developed for digital images using PRNU [3-12], less research has been conducted towards the forensic analysis of videos. Chen et al. [13] were the first authors to extend their PRNU technique [3] from an image to video and demonstrated that PRNU can be used to link a video to its source camcorder effectively. In this approach, the PRNUs are extracted from both (training and testing) video clips using MLE as shown in (2). Then, the peak-to-correlation energy (PCE) is utilized as measurement to detect the presence of PRNU. The main idea behind PCE is to consider the correlation between the PRNU and shifted versions of the noise residue to lessen the similarity which may exist between the PRNU of a specific digital device and the noise residue of

an image taken by a different camera. The PCE measure is defined in [4] and [13] as:

$$PCE(x,y) = \frac{C_{xy}^2(0,0)}{\frac{1}{\omega \times \nu - |A|} \sum_{m1,m2 \notin A} C_{xy}^2\,(m1,m2)} \qquad (3)$$

where A is a small neighbor area of size 11 × 11 around the central point at (0,0), $|A|$ is the number of pixels in A, and C_{xy} $(m1,\ m2)$ represents the circular cross-correlation. In [14] confidence weight PRNU based on image gradient magnitudes is proposed in order to improve PRNU estimation and evaluate the impact of video content on the performance of Chen et al. [13]. In [15] the video frames are resized to 512×512 using bilinear interpolation and the PRNU is extracted only from the green channel by averaging the residual signal over all frames. Current video coding standards such as H.264, MPEG, or latest version, use three types of video frames, which are intra-coded frame (I-frame), predictive coded frame (P-frame), and bi-predictive coded frame (B-frames)[14]. Chuang et al. [16] analysed the video compression impact on PRUN estimation in the compressed domain and reported that extracting the PRNU from I-frames is more reliable than P-frames and B-frames [14],[16]. Later, a PRNU-based technique for out-of-camera stabilized videos, such as cropping, and rotation processing is proposed by Taspinar et al. [17]. In this technique also 50 I-frames are extracted from each video in order to estimate the PRNU. A smartphone may automatically rotate the video 180 degrees while recording videos with rolling 180 degrees. The authors In [18] are focused on effect of cameras rolling ,whether videos with several rolling degrees, 0, 90, 180, and 270 degrees, can affect the PRNU analysis or not. In [19], a hybrid methodology that utilizes both videos and still images are introduced to estimate the PRNU. In this technique, 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 [20], the authors outlined the possible factors such as Compression, resolution and length of the video, which could influence a decrease of the PRNU's correlation value in videos. Although there have been previous studies [3]-[20] provided in order to improve the efficiency of source smartphone identification based on PRNU, an efficient approach that takes into account the frame content is still lacking. Furthermore, existing techniques that consider the effect of lossy compression on the estimation of PRNU in the compressed domain requires full access to the right decoder in order to have separate I-frames at the estimation of the PRNU. This is not always handy given the large number of video codecs used in smartphones and released with different versions as standalone applications. This paper addresses the problem of source smartphone video identification based on PRNU estimation. The traditional approach to estimate the PRNU in digital videos use all video frames [13],[14],[15],[17]. In this paper, a new approach based on detecting smooth video frames while discarding the textured ones for efficient PRNU estimation is proposed. Experimental results on a video dataset, acquired by various smartphones, have shown a significant gain obtained with the proposed approach over the conventional state-of the-art smartphone identification scheme using different sizes of frames. The rest of this paper is structured as follows; Section II describes the proposed method. Experimental results and analysis are provided in Section III. A conclusion is drawn in Section IV.

II. PROPOSED PRNU ESTIMATION APPROACH

Fig. 1 illustrates the proposed source smartphone video identification and verification scheme. The rationale behind the proposed idea is that the PRNU is hard to estimate in textured and contoured regions [4],[14]. This is because the PRNU is intensively present in the high frequency range which also characterises the frequency content of textured and edged areas. Also, due to the lossy compression nature in which digital videos are stored, distortions mainly occur in such textured and edged regions since the human visual system is less sensitive to changes in such regions. As a result, the PRNU noise gets significantly affected in those regions and its estimation becomes inaccurate. Therefore, selecting frames based on their content would be sensitive to enhance the estimation of the PRNU. First, frames are extracted from each video and converted to grey level. Then, the proposed selection method is applied to separate the frames through feature extraction and machine learning into textured and non-textured frames. Next, only the non-textured frames are selected for PRNU estimation. Each smartphone PRNU is stored in a database to be used later for verification and identification. It is worth mentioning that, in this work, the proposed frame selection method is applied only in training stage. This is due the fact that, in real scenarios, the query video may be highly textured with very few or even without smooth frames. Therefore, at the smartphone PRNU matching stage, the PRNU is estimated from all the available frames in the query video. In identification, a query video PRNU is compared to all PRNUs stored in the database using the PCE similarity measure. The closest PRNU is said to correspond to the smartphone which has been used to record the video. In smartphone verification, however, the similarity between the query video PRNU and the PRNU of a certain smartphone is compared to a given threshold in order to verify whether the video is recorded by that smartphone. The proposed frame selection method components will be discussed in more detail in the next subsections.

A. *Frame Texture Features*

In the past decades, textural characteristics in images, have been broadly studied as one of the most important features present in pictures and can be used for classification, segmentation, feature extraction [21]. In this work, the features of grey level co-occurrence matrix (GLCM) [22] are used in order to extract second order statistical texture features for each frame.

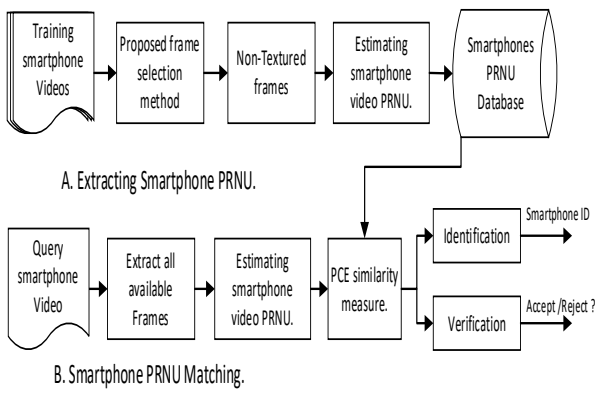

Fig. 1. High-level of the proposed source smartphone video identification and verification system.

GLCM can be seen as a matrix which characterises the relative frequencies of a pair of grey levels that appear at distance d (from 1 to size of image) apart and at a particular angle Θ (0°, 45°, 90° and 135°). Fig. 2 illustrates how GLCM can be calculated from 4-by-5 image J for d =1 and Θ=0° [23]. Fourteen features were obtained in [22] from the GLCMs to characterise texture, these features can be calculated at different angles. In this work, six texture features are used, which are: correlation, contrast, standard deviation, homogeneity, energy, and entropy [24]. Table I briefly describes these features and its formulas [25], where G refers for the number of the grey levels in the frame, $P_d^{\theta}(i,j)$ refers to $(i,j)^{th}$ entry in the GLCM that represent the probability of existence of pixel pairs at certain angle and distance. The reader is referred to [22] for more information about GLCMs and its features.

B. *Frame selection method for PRNUs extraction.*

This method aims to discard the highly textured frames which may lead to contribute negatively to the estimation of the PRNU as discussed earlier. Fig. 3 illustrates the main components of the proposed frame selection method.

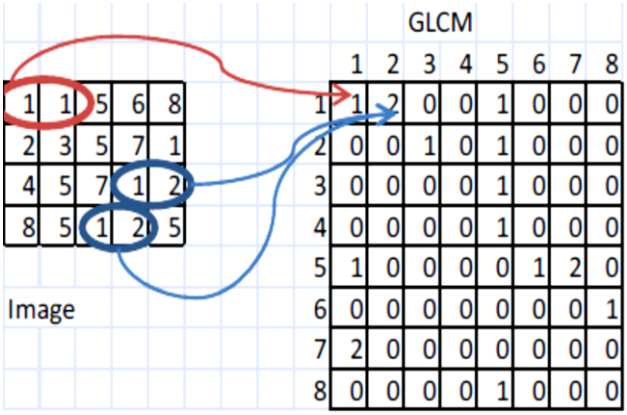

Fig. 2. GLCM calculation from 4-by-5 image I [23].

In phase 1, frames taken from a large number of different training videos recorded by different devices, supposedly accessible to the forensic investigator, and then the GLCM is used to obtain the frame features (correlation, contrast, standard deviation, homogeneity, energy, and entropy). It is worth mentioning that the GLCM is used with a distance d that is equal to 1, while Θ is considered in four directions Θ (0°, 45°, 90° and 135°). This process will give us four GLCM matrixes (one in each direction) in order to obtain more statistical information for each frame. Next, the mean of each of these GLCM features is calculated over the four directions. This process is repeated for each smartphone video frame, and then the GLCM feature vectors are used to feed a k-Means clustering algorithm [26] in order to separate them into two clusters (i.e., textured and non-textured frames). The value of k=2 here represents the two clusters of textured and non-textured frames. The obtained k=2 centroids (one centroid for each cluster) will be used to identify non-textured frames in phase two for PRNU estimation. The purpose of the first phase is to split the feature space into two sub-spaces, i.e., textured, and non-textured sub-spaces via unsupervised learning using the GLCM texture features. The two obtained centroids are meant to represent the centers of the feature sub-spaces describing textured and non-textured frames. In the second phase, the GLCM features are extracted from each frame of the available smartphone videos for PRNU estimation in the same fashion. Unlike in phase 1, however, these videos are recorded by the same smartphone device. Then, each frame is classified into a textured or non-textured frame by calculating the Euclidean distance between GLCM features and the two centroids representing the two aforementioned clusters. The smallest distance is used to assign the frame to one of the existing clusters. Finally, only the non-textured frames are used to extract the PRNU. Once the PRNU is estimated for each smartphone device, the process of identification or verification is conducted as explained earlier (See Fig. 1).

TABLE I. FEATURES OF GLCM.

Features Description	Formulas
Contrast is measure of the intensity contrast between a pixel and its neighbor over the whole frame. If there is a high amount of variation the contrast will be high. A value of 0 indicates a constant video frame.	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\lvert i-j\rvert^2\, p_d^{\theta}(i,j)$
Homogeneity gives a measure of the similarity in the frame. A value of 0 indicates a strong similarity in the video frame.	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{1}{1+(i-j)^2}\, p_d^{\theta}(i,j)$
Entropy is a statistical measure of randomness that could be utilized to characterize the texture of the video frame.	$-\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} p_d^{\theta}(i,j)\log_2\left(p_d^{\theta}(i,j)\right)$
Energy can be used to measure the textural uniformity of the frame. It also can help to determine disorders in texture.	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\left[p_d^{\theta}(i,j)\right]^2$
Correlation is to provide, how a pixel is correlated to its neighbouring pixels.	$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{ij\, p_d^{\theta}(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$

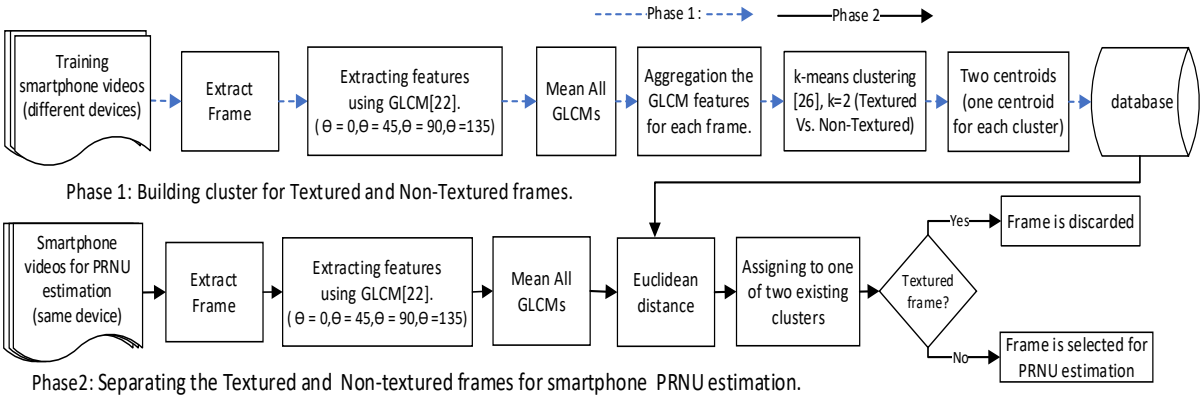

Fig. 3. The proposed frame selection method for video smartphone identification and verification system.

III. EXPERIMENTAL RESULTS

In this section, the efficiency of the proposed approach is evaluated against the previously mentioned traditional approach. The assessment has been conducted using the Video Authentication and Camera Identification Database (Video-ACID) [11]. Although this dataset contains videos from different devices such as smartphones, tablets, digital cameras and digital camcorders, the aim of this work is to examine the performance on videos with low resolutions that were recorded with smartphones. Table II demonstrates the ten smartphones which have been used in our experiments. The unsupervised learning process uses all frames from 200 randomly selected videos recorded by different smartphones. In order to estimate the PRNU, 50 videos per smartphone are used to estimate the PRNU, while the remaining videos are used in the testing stage. The extraction of PRNU has been carried out by considering cropped blocks from the frame with different sizes, i.e., 512 × 512 and 1024 × 1024. The blocks are cropped from the center of the full-size frame without affecting their content. Here, it is meant by the traditional approach the techniques that use all video frames to estimate the PRNU [13],[14],[15],[17]. The well-known wavelet-based Wiener filter [3] has been used to estimate the PRNU in both the traditional and proposed approaches. In the first set of experiments, we evaluate the changes in the peak (PCE values) that describes the similarity between two PRNUs of the same smartphones for each approach (the proposed vs traditional approach), the PCE is calculated as shown in (3) between the PRNU estimated from query videos (about 1800 clips) and the actual PRNU estimated from reference videos. The results show that the proposed approach has the higher peaks in comparison to the traditional approach for most of the tested videos. The average PCE values for all testing videos in the traditional approach was 72, while in the proposed approach was around 83. This enhancement in the peak values is clear in Fig. 4, when about 100 videos are randomly selected. In the second set of experiments, we assess the performance of the proposed system in two different aspects, i.e., source identification and source verification.

TABLE II. SMARTPHONES USED IN THE EXPERIMENTAL

Smartphone name	Symbol	number of videos
Apple iPhone 8 plus	M01	223
Huawei Honor 6X (A)	M02	238
Huawei Honor 6X (B)	M03	238
LG Q6	M04	260
LG X Charge	M05	234
Samsung Galaxy J7 Pro (A)	M06	239
Samsung Galaxy J7 Pro (B)	M07	169
Samsung Galaxy S3	M08	230
Samsung Galaxy S5	M09	257
Samsung Galaxy S7	M10	206

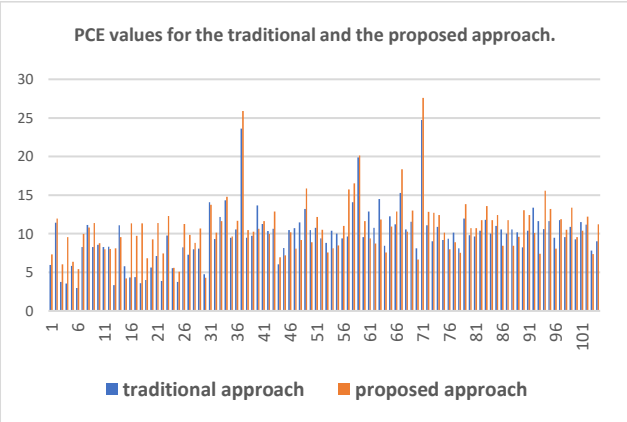

Fig. 4. PCE values for the traditional and the proposed approach.

A. *Source smartphone identification:*

In source smartphone identification, the forensic analyst possesses several smartphones, and the aim is to identify the smartphone used to take a video. Here, it is supposed that the video is acquired by one of the smartphones available. Consequently, a query video is assigned to a specific smartphone if the corresponding PRNU provides the highest PCE. Table III illustrates the false negative rate (FNR) for each smartphone using a frame size of 512×512 and 1024×1024. A clear enhancement is shown in most of smartphones for instance the FNR has been reduced from 64.74% to 26.01%, 43.09% to 22.34 %, and from 20.77% to 4.35 %. when frame sizes are equal to 512×512. Furthermore, another example of / Additionally, as shown in table IV, the proposed technique leads to a reduction in the overall false positive rate (FPR) regardless of the size of the frame.

TABLE III. FNR(%) FOR EACH SMARTPHONE USING THE TRADITIONAL AND PROPOSED APPROACH.

frame size	methods	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10	overall FNR
512×512	Traditional approach	64.74	43.09	11.70	**48.57**	45.65	1.06	0.00	12.22	20.77	0.64	24.84
	Proposed approach	**26.01**	**22.34**	**4.26**	69.52	**5.98**	1.06	0.00	**7.78**	**4.35**	0.64	**14.19**
1024×1024	Traditional approach	64.74	60.11	14.89	**29.05**	64.09	2.12	0.00	9.44	20.77	2.56	26.78
	Proposed approach	**39.31**	**22.87**	**2.13**	49.05	**2.76**	**1.06**	0.00	**5.56**	**10.63**	**1.92**	**13.53**

TABLE IV. FPR(%) FOR EACH SMARTPHONE USING THE TRADITIONAL AND PROPOSED APPROACH.

frame size	methods	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10	overall FPR
512×512	Traditional approach	0.68	0.12	**0.19**	0.38	11.18	**0.19**	2.21	3.10	8.00	3.05	2.91
	Proposed approach	**0.62**	**0.00**	0.25	**0.13**	**9.13**	0.50	**1.55**	**1.36**	**1.95**	**1.71**	**1.72**
1024×1024	Traditional approach	1.36	**0.00**	0.56	2.02	12.80	**0.25**	4.25	3.35	5.18	**1.10**	3.09
	Proposed approach	**1.24**	0.06	**0.37**	**0.25**	**7.76**	1.12	**1.44**	**0.31**	**2.40**	1.16	**1.61**

Although table III and table IV indicate that the proposed approach does not always give an improvement for every smartphone, the overall FNR and FPR of the proposed approach exceeds that with the traditional approach. This is true for all frame sizes as shown in table III and table IV. In addition, the proposed approach provides less miss-identification rates when compared with the traditional one by approximately 50% regardless of the frame size, as shown through the mean of FNR and FPR (see table III and IV) calculated for each smartphone. The overall error has been reduced from 13.88% to 7.96% and from 14.93% to 7.92%, respectively.

B. Source smartphone verification:

In source smartphone verification, the task of the forensic analyst is to verify whether a smartphone has been acquired a video evidence by a given threshold. This threshold represents the least possible similarity between the reference PRNU of a smartphone and the PRNU of a video acquired by the same device. This mean that measuring the performance of the system by calculating the false positive rate and false negative rate for each threshold value. This leads us to use what is known in the literature as the Receiver Operating Characteristics (ROC) curve. In this section, 10 smartphones have been used to determine the PCE values of similarity between each smartphone PRNU and the PRNU of videos recorded by different smartphones. On the other hand, the PCE values of similarity between every smartphone PRNU and the PRNU of video acquired by the same smartphone have been calculated. This will enable us to determine the false positive rate and false negative rate for each threshold value and then draw the ROC. The ROC curve performance of the proposed approach along with the traditional approach is demonstrated in Fig. 5 and Fig. 6. The ROC curve show that the proposed method performs better than traditional approach. This is true for all frame sizes.

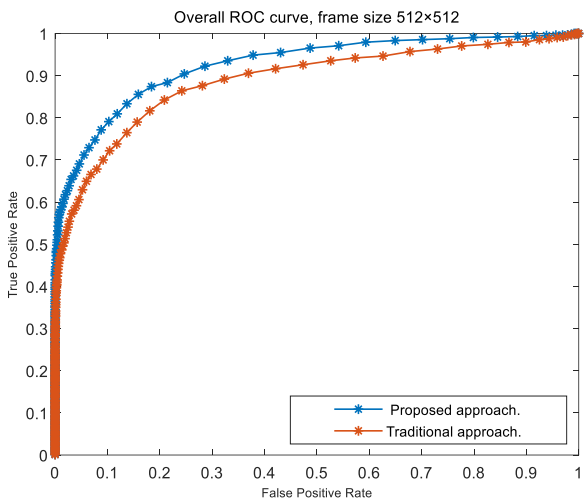

Fig. 5. Overall ROC curve for 10 smartphones, frame size 512×512.

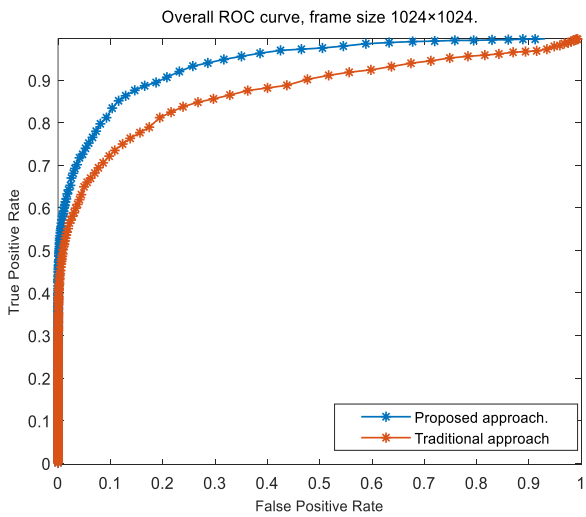

Fig. 6. Overall ROC curve for 10 smartphones, frame size 1024×1024.

IV. CONCLUSION

In this paper, an efficient source smartphone identification and verification approach has been introduced. The residual signals extracted from video frames and used to estimate the PRNU are viewed as noisy observations of the PRNU, but the averaging process attenuate the effect of undesirable noise. Such undesirable noise can be due to frame characteristics (textured, edged, etc.) as well as distortions due to lossy compression that can mainly affect textured and edged frame contents. Different from the traditional approach, the proposed scheme aims to enhance the PRNU estimation by discarding the highly textured frames that may contribute negatively to the estimation of the PRNU. Experimental analysis covering two application scenarios in smartphone video forensics has shown the superiority of the proposed system over a related state-of-the-art technique.

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