Impact of Photometric Transformations on PRNU Estimation Schemes: A Case Study Using Near Infrared Ocular Images

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Abstract—The principle of Photo Response Non Uniformity (PRNU) is often used to link a digital image with the sensor that produced it. In this regard, a number of schemes have been proposed in the literature to extract PRNU details from a given input image. In this work, we study the impact of photometric transformations applied to near-infrared ocular images, on PRNU-based iris sensor identification accuracy. The contributions of this work are as follows: (a) Firstly, we evaluate the impact of 7 different photometric transformations on 4 different PRNU-based sensor identification schemes; (b) Secondly, we develop an explanatory model based on the Jensen-Shannon divergence measure to analyze the conditions under which these PRNU estimation schemes fail on photometrically transformed images. The analysis is conducted using 9,626 ocular images pertaining to 11 different iris sensors. Experiments suggest that (a) the Enhanced Sensor Pattern Noise and Maximum Likelihood Estimation based Sensor Pattern Noise techniques are more robust to photometric transformations than other PRNU-based schemes; (b) the application of photometric transformations actually improves the performance of the Phase Sensor Pattern Noise scheme; (c) the single-scale Self Quotient Image (SQI) and Difference of Gaussians (DoG) filtering transformations adversely impact all 4 PRNU-based schemes considered in this work; and (d) the Jensen-Shannon divergence measure is able to explain the degradation in performance of PRNU-based schemes as a function of the photometrically modified images.

I. INTRODUCTION

The field of digital image forensics uses scientific principles to establish the origin and authenticity of digital images [1]. The proliferation of digital images in a number of applications, ranging from social media [2] to law enforcement [3, 4], has further accentuated the need to develop effective image forensic tools for a myriad of purposes. One such tool involves the extraction of sensor-specific details from digital images in order to determine the origin of the image, i.e., the sensor that produced the image. This process, referred to as sensor forensics or sensor identification or device validation, aids in creating a link between an image and its source [5, 6]. One of the most popular methods in the literature for sensor forensics is the so-called PRNU (Photo Response Non Uniformity) method [7], which looks for sensor-specific artifacts in digital images (see Figure 1). More specifically, PRNU-based schemes assume that defects in the sensor manufacturing process result in non-uniform response of individual pixels to similar illumination levels, and that these non-uniformities (manifesting as sensor noise pattern) can be extracted from the image.

While such sensor forensic schemes have been extensively studied in the context of color images produced by classical digital cameras based on CMOS or CCD technology [7–10], their applicability to near-infrared (NIR) sensors was only recently established particularly in the context of iris and ocular recognition systems [11]–[16]. In such recognition systems, often, the input ocular image is subjected to some illumination normalization schemes in order to address issues such as motion blur, out-of-focus imaging, low resolution and uneven illumination [17]. See Figure 2. The goal of such illumination normalization schemes is to improve the biometric recognition accuracy.

In this work, we examine the following question: Do these commonly applied photometric transformation schemes impede the performance of iris sensor identification algorithms? Such a study has the following benefits:

1. It would help in better understanding the robustness of different PRNU-based schemes to commonly applied illumination normalization routines in the iris recognition domain. This is particularly important in situations where the original raw image is not available for forensic purposes, but the processed image is available (e.g., when pre-processing is accomplished using hardware).

2. In recent literature, the possibility of combining ocular biometric recognition with device (sensor) identification has been proposed for enhanced security [18], by using the same ocular image for both device identification and ocular recognition. Since the photometric normalization schemes considered in this work are known to positively impact biometric recognition, it behooves us to determine the nature of their impact on device identification.

In this work, we evaluate the effect of photometric transformation on multiple PRNU-based sensor identification techniques, and use Jensen-Shannon based divergence measure to explain the rationale behind the variation in sensor identification performance.

The rest of the paper is organized as follows: Section II provides a brief literature review on PRNU-based sensor identification schemes. Section III describes the illumination normalization schemes and the PRNU estimation schemes.
used in this work. Section IV describes the datasets and experiments, and summarizes the results. Section V presents the explanatory model that analyzes the results in a quantifiable manner. Section VI concludes the paper.

II. RELATED WORK

Sensor identification [1] is an active field of research; early work extracted information related to dead pixels [5] and color filter array interpolation artifacts [6] to link an image to its source of origin, i.e., the device that acquired the image. This link can also be established using the Sensor Pattern Noise (SPN) [7]–[10], which arises due to manufacturing defects in the silicon wafer used for sensor construction. The fundamental component of SPN is Photo Response Non-Uniformity (PRNU), which is a consequence of the non-uniform variation in the sensitivity of individual pixels to the same light intensity. The PRNU pattern manifests in the images acquired using the sensor, thereby serving as a unique sensor identifier. PRNU has been extensively studied in the context of RGB sensors [8, 19]–[21].

However, iris sensors (see Figure 3) typically operate in the near-infrared (NIR) spectrum and have different constructional and operational details [22]. NIR images have been shown to be statistically different from images captured in the visible spectrum [23]. In spite of these differences, recent research has demonstrated that PRNU-based schemes developed for RGB images can be applied to NIR iris images [12]–[15].

A review of the literature suggests that there has been limited research on the impact of photometric transformations on sensor identification algorithms [7] [24]. In the current work, we advance our understanding of PRNU-based sensor identification schemes by considering multiple photometric transformations and analyzing the effect of such transformations on sensor identification accuracy, in the context of NIR ocular images. Further, we develop an explanatory model to determine a causal relationship between photometric transformations and their impact on the performance of PRNU algorithms.

The principal contributions of this work are as follows: a) investigating the effect of seven illumination normalization schemes (the terms illumination normalization, photometric transformation and image enhancement have been used interchangeably in the paper) on sensor identification performance; b) conducting experiments using 11 sensors and 4 PRNU estimation schemes; and c) using the Jensen-Shannon divergence measure to explain the impact of photometric transformations on the wavelet denoised pixel intensity distribution (discussed later) and, subsequently, on sensor identification.

III. ILLUMINATION NORMALIZATION SCHEMES AND SENSOR IDENTIFICATION METHODS

In this section, we will discuss the seven ocular image enhancement schemes considered in our work, followed by a brief overview of the four PRNU-based sensor identification strategies.

A. Photometric Transformation

Variations in ambient lighting conditions, coupled with unconstrained image acquisition, result in challenging ocular images as depicted in Figure 2. Occlusions due to eyelid movement, motion blur, de-focus blur, poor resolution and varying degrees of illumination can significantly impact iris segmentation and iris recognition processes [17]. A large number of illumination normalization schemes have been demonstrated to improve iris and periocular recognition performance [17] [25]–[27]. The relevance of the seven ocular image enhancement schemes considered in our work is discussed next.

Homomorphic Filtering: Homomorphic filtering is most commonly used for removing non-uniform illumination in images. Here, it is used for image enhancement purposes. It is a technique that modifies the frequency response of an image to reduce the effects of non-uniform illumination or to improve the contrast of an image.

Fig. 1: General framework of a PRNU-based sensor identification system.

Fig. 2: Examples of NIR ocular images exhibiting (a) defocus blur, (b) uneven illumination and (c) motion blur (due to eyelid movement).
Gamma correction: Gamma adjustment is typically used to increase the contrast of images acquired in low illumination conditions. Issues arising due to uneven illumination, as depicted in Figure 2(b), can be addressed by applying a high-pass Butterworth filter after the logarithm-transformed image is converted to the frequency domain using Fourier transform. Singh et al. [25] used homomorphic filtering to improve the performance of iris recognition on the NHCI database.

Gamma correction: Gamma adjustment is typically used to increase the contrast of images acquired in low illumination conditions. This photometric transformation produces the output image as a power, denoted by a parameter $\gamma$, of the input image pixel values. Jiilela et al. [17] employed gamma correction for improving the contrast of images in the FOCS database for periocular recognition. The range of $\gamma$ used in our work is [0.1, 2.1].

Contrast Limited Adaptive Histogram Equalization (CLAHE): Histogram equalization has been shown to aid periorocular recognition [21]. CLAHE tessellates the image into patches and performs adaptive histogram equalization on each of these patches by clipping the pixel intensity values exceeding the user defined contrast limit [22]. Finally, it aggregates the patches using bilinear interpolation. In our experiments, $8 \times 8$ patches are considered and the contrast limit is set to 0.01.

Discrete Cosine Transform (DCT): Illumination invariance can be achieved by applying DCT transform to the logarithm-transformed image, followed by removal of the low frequency DCT coefficients, which capture the illumination component of the image [23, 24]. \ This process operates like a high pass filter. Juefei-Xu and Savvides applied this illumination normalization for robust periorocular recognition on NIST's FRGC version 2 database [27].

Difference of Gaussians (DoG): DoG filter closely approximates the Laplacian of Gaussian (LoG) filter in a computationally efficient manner [35]. DoG uses Gaussian filters having different scales or filter sizes. The difference between the two filtered outputs, corresponding to Gaussian filtering of the image using two different scales, is computed. This difference is devoid of the illumination variations present in the original image. DoG filtering has been used to compensate for illumination variations in the context of periorocular recognition on the FRGC version 2 database [27]. The two filter sizes used in our work are $\sigma_1 = 1$ and $\sigma_2 = 2$, where $\sigma_i$ denotes the standard deviation.

Multi-Scale Retinex (MSR): Multi-Scale Retinex (MSR) [36] uses smoothing kernels of different sizes, and combines the outputs of Single Scale Retinex (SSR) to remove the halo-like artifacts produced in images transformed using a single-scale kernel. The retinex algorithm has been applied to UBIRIS v2, FRGC and CASIAv4-Distance datasets to improve the quality of ocular images [37]. MSR proved to be the best illumination normalization scheme in [27]. Three scales (standard deviations), viz., $\sigma = [7, 15, 21]$, were used in our work to retain the fine details present in the scene as well as maintain the visual aesthetics of the image.

Single-Scale Self Quotient Image (SQI): SQI is closely related to MSR. It is based on the Lambertian model and the concept of quotient image [38]. The illumination invariant representation can be obtained as the quotient of the original image and the smoothed version of the original image. The halo-like artifacts produced in MSR is typically due to the use of an isotropic Gaussian smoothing kernel. This problem is resolved in SQI using a weighted anisotropic Gaussian smoothing kernel [38]. SQI was used for illumination normalization on the UBIPosePr dataset for unconstrained periorcular recognition [39].

Figure 4 illustrates the effect of the aforementioned photometric normalization schemes on a sample ocular NIR image. As evident from Figure 4(e), MSR is not able to remove
the halo artifacts completely, and these anomalies persist in Figure 4(g), where DCT based normalization scheme is used.

B. PRNU Estimation Schemes

A sensor identification algorithm uses example ocular NIR images from a specific sensor (or camera or device) as training data and generates a reference pattern from this data, which serves as a template for that sensor. When a test image is presented, the algorithm extracts a noise residual from this image and compares it against the sensor reference pattern, i.e., the template, to generate a similarity score. Normalized Cross-Correlation (NCC) is used to measure the degree of similarity between the sensor reference pattern and the test noise residual (see Figure 1). There are multiple PRNU estimation algorithms as discussed in [40], but in this work we will primarily focus on the following four schemes.

Basic SPN: PRNU is estimated by denoising the image using Daubechies Quadature Mirror Filter in [7]. The denoised image is then subtracted from the original image to compute the noise residuals. Basic SPN is based on the underlying premise that PRNU is a dominant multiplicative term, which can be isolated by denoising the image using a wavelet based filter. The denoising filter suppresses scene influences present in the image and recovers the sensor imprint manifested as the noise residual. The sensor reference pattern is computed as average of the noise residuals extracted from the training images.

MLE SPN: Artifacts arising due to color filter array present in RGB sensors, strong JPEG compression or sensor-specific oddities, may produce a higher rate of false matches. The Maximum Likelihood Estimation (MLE) method uses Wiener filtering and zero-mean operations to compute an accurate estimate of the PRNU [8]. The noise residuals are \( L_2 \)-normalized as suggested in [13], and then a weighted average is used to construct the sensor reference pattern.

Enhanced SPN: Li [41] pointed out that scene influences can potentially corrupt the noise residual of a single test image to a greater extent than the reference pattern, since the latter averages multiple noise residuals. The author proposed five enhancement models that use analytical functions to adaptively regulate the magnitude of the noise coefficients extracted in the wavelet domain. The enhancement models selectively attenuate the wavelet coefficients representing the scene influences, thus strengthening the noise residual of a single test image. Analytical Model 3 used in this work is given below:

\[
n_e(i, j) = \begin{cases} 
1 - e^{-n(i,j)}, & \text{if } 0 \leq n(i, j) \leq \alpha; \\
(1 - e^{-\alpha})(e^{\alpha-n(i,j)}), & \text{if } n(i,j) > \alpha; \\
-1 + e^{n(i,j)}, & \text{if } -\alpha \leq n(i, j); \\
& \text{if } -\alpha > n(i, j) < 0; \\
(-1 + e^{-\alpha})(e^{\alpha+n(i,j)}), & \text{if } n(i, j) < -\alpha.
\end{cases}
\]

Here, \( n(i, j) \) and \( n_e(i, j) \) indicate the original and enhanced noise residual values, respectively, and \( i \) and \( j \) are the indices of the noise residual in the wavelet domain, and \( \alpha \) denotes a user-defined threshold which is set to 6 in this paper. The sensor reference pattern is identical to the one used for Basic SPN. The enhancement model is applied only to \( L_2 \)-normalized test noise residuals.

Phase SPN: Assuming that the SPN is a white Gaussian noise, Kang et al. [19] hypothesized that extraction of the phase component of the PRNU in the Fourier domain would be an effective representation of the SPN. We did not perform spectral whitening of training noise residuals, unlike [19], as spurious influences arising due to varying scene content are not likely to be present in NIR ocular images depicting a homogeneous scene (the ocular region).

IV. EXPERIMENTS AND RESULTS

In this section, we review the datasets used in our work, followed by a discussion of the results.

A. Datasets

We used 11 iris datasets corresponding to 11 different sensors. The details concerning the sensors and the datasets are outlined in Table I. The sensor reference pattern is generated using 55 training images per sensor and the number of test images varied from 528 to 940 per sensor. The subjects in the training and test sets were mutually exclusive.

B. Results and Analysis

Experiments were conducted on 9,626 images (605 for training and 9,021 for testing) and the results are reported in terms of Rank 1 identification accuracy. Rank 1 accuracy corresponds to the proportion of test images assigned to the correct sensor class, i.e., those images whose noise residuals yield the highest NCC when compared against the reference pattern of the sensor they actually originated from. Note that in all experiments, the sensor reference pattern was always computed using the original training images and not the photometrically modified images. Table II reports the sensor identification accuracies for each PRNU method. Inferences drawn from this table are presented below:

- **Observation#1**: The application of photometric transformations marginally decreases the sensor identification performance of the 4 PRNU estimation schemes considered in this work. Note that the photometric schemes considered herein are applicable in the context of iris and periocular recognition.
- **Observation#2**: Enhanced SPN emerges to be the most robust to illumination normalization methods among the 4 PRNU estimation schemes, closely followed by MLE SPN. The robustness is assessed by computing the average of the rank-1 sensor identification accuracies corresponding to the 7 photometric transformations. Enhanced SPN resulted in the highest average identification accuracy of 95.99% followed by MLE SPN with an average of 95.97%. Basic SPN yielded 94.90% and Phase SPN resulted in 94.63%.

### TABLE I: The datasets and sensors used in this work.

<table>
<thead>
<tr>
<th>Name of Dataset</th>
<th>Name of Sensor</th>
<th>Abbreviation</th>
<th>Image Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>BioCOP2009 Set I</td>
<td>Aoptix Insight</td>
<td>Aop</td>
<td>640x480</td>
</tr>
<tr>
<td>CASIAv2 Device1</td>
<td>OKI IrisPass-h</td>
<td>OKI</td>
<td>640x480</td>
</tr>
<tr>
<td>CASIAv2 Device2</td>
<td>CASIA IrisCam V2</td>
<td>IC</td>
<td>640x480</td>
</tr>
<tr>
<td>CASIAv4 (CASIA-Iris Thousand subset)</td>
<td>IrisKing IREMB100</td>
<td>IK</td>
<td>640x480</td>
</tr>
<tr>
<td>HITD [43]</td>
<td>JIRIS JPC1000</td>
<td>JPC</td>
<td>320x240</td>
</tr>
<tr>
<td>MMU2 [45]</td>
<td>Cogent</td>
<td>Cog</td>
<td>640x480</td>
</tr>
<tr>
<td>ND_Cosmetic_Contact_Lenses_2013 [46]</td>
<td>Panasonic BM-ET 100US Authenticam</td>
<td>Pan</td>
<td>320x238</td>
</tr>
<tr>
<td>ND-Cross-Sensor-Iris-2013 Set I [46]</td>
<td>IrisGuard-IG-AD100</td>
<td>AD</td>
<td>640x480</td>
</tr>
<tr>
<td>ND-Cross-Sensor-Iris-2013 Set II [46]</td>
<td>LG2200</td>
<td>LG22</td>
<td>640x480</td>
</tr>
<tr>
<td>WVU Off-Axis [47]</td>
<td>LG4000</td>
<td>LG40</td>
<td>640x480</td>
</tr>
<tr>
<td>EverFocus Monochrome CCD</td>
<td></td>
<td>Mon</td>
<td>640x480</td>
</tr>
</tbody>
</table>

### TABLE II: Rank-1 Sensor Identification Accuracies (%). The value enclosed in parentheses indicates the difference in accuracy when compared to that obtained using the original images. Note that in all cases, the reference pattern for each sensor is computed using the unmodified original images.

<table>
<thead>
<tr>
<th>Photometric Transformation</th>
<th>Basic SPN</th>
<th>Enhanced SPN</th>
<th>Phase SPN</th>
<th>MLE SPN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>96.43</td>
<td>98.87</td>
<td>94.89</td>
<td>97.10</td>
</tr>
<tr>
<td>Homomorphic</td>
<td>92.38±(4.05)</td>
<td>93.38±(5.49)</td>
<td>93.31±(1.52)</td>
<td>97.79±(4.69)</td>
</tr>
<tr>
<td>CLAHE</td>
<td>95.75±(0.68)</td>
<td>97.78±(1.09)</td>
<td>94.51±(0.38)</td>
<td>96.43±(0.67)</td>
</tr>
<tr>
<td>Gamma</td>
<td>96.53±(0.10)</td>
<td>98.03±(0.84)</td>
<td>95.41±(0.52)</td>
<td>97.60±(0.50)</td>
</tr>
<tr>
<td>DCT normalization</td>
<td>95.54±(0.89)</td>
<td>97.01±(1.86)</td>
<td>96.20±(1.31)</td>
<td>97.35±(0.25)</td>
</tr>
<tr>
<td>DoG</td>
<td>92.81±(3.62)</td>
<td>92.77±(6.10)</td>
<td>90.28±(4.61)</td>
<td>90.42±(6.68)</td>
</tr>
<tr>
<td>MSR</td>
<td>96.31±(0.12)</td>
<td>96.18±(2.69)</td>
<td>98.16±(3.27)</td>
<td>98.20±(1.10)</td>
</tr>
<tr>
<td>SQI</td>
<td>95.04±(1.39)</td>
<td>96.82±(2.05)</td>
<td>94.47±(0.42)</td>
<td>94.00±(3.10)</td>
</tr>
</tbody>
</table>

### TABLE III: Jensen-Shannon divergence between the wavelet denoised versions of the original and photometrically transformed images.

<table>
<thead>
<tr>
<th>Transformations</th>
<th>Aop</th>
<th>OKI</th>
<th>IC</th>
<th>IK</th>
<th>JPC</th>
<th>Cog</th>
<th>Pan</th>
<th>AD</th>
<th>LG22</th>
<th>LG40</th>
<th>Mon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original-CLAHE</td>
<td>0.5543</td>
<td>0.1018</td>
<td>0.2092</td>
<td>0.1053</td>
<td>0.3165</td>
<td>0.0982</td>
<td>0.4027</td>
<td>0.4403</td>
<td>0.4465</td>
<td>0.6798</td>
<td>0.0912</td>
</tr>
<tr>
<td>Original-DoG</td>
<td>0.5325</td>
<td>0.0124</td>
<td>0.1330</td>
<td>0.0824</td>
<td>0.5179</td>
<td>0.1033</td>
<td>0.3522</td>
<td>0.3402</td>
<td>0.3314</td>
<td>0.3838</td>
<td>0.0971</td>
</tr>
<tr>
<td>Original-Gamma</td>
<td>0.4791</td>
<td>0.0097</td>
<td>0.1370</td>
<td>0.0754</td>
<td>0.3074</td>
<td>0.0760</td>
<td>0.3134</td>
<td>0.2516</td>
<td>0.3263</td>
<td>0.3230</td>
<td>0.0397</td>
</tr>
<tr>
<td>Original-Homomorphic</td>
<td>0.4559</td>
<td>0.0836</td>
<td>0.0960</td>
<td>0.0599</td>
<td>0.2310</td>
<td>0.1143</td>
<td>0.2282</td>
<td>0.2399</td>
<td>0.3062</td>
<td>0.2561</td>
<td>0.1036</td>
</tr>
<tr>
<td>Original-MSR</td>
<td>0.5602</td>
<td>0.1231</td>
<td>0.1657</td>
<td>0.2409</td>
<td>0.7459</td>
<td>0.0910</td>
<td>0.4060</td>
<td>0.5882</td>
<td>0.5440</td>
<td>0.4311</td>
<td>0.0678</td>
</tr>
<tr>
<td>Original-SQI</td>
<td>0.7320</td>
<td>0.1191</td>
<td>0.2915</td>
<td>0.1880</td>
<td>0.3522</td>
<td>0.1361</td>
<td>0.5478</td>
<td>0.6849</td>
<td>0.5867</td>
<td>0.8173</td>
<td>0.1304</td>
</tr>
</tbody>
</table>

- **Observation#3**: Photometric transformations were observed to improve the sensor identification accuracy of the Phase SPN method. Multi-Scale Retinex improved the accuracy by 3.27%, DCT normalization boosted the accuracy by 1.31% and Gamma correction marginally improved it by 0.52%.

- **Observation#4**: DoG filtering resulted in degradation of sensor identification accuracy by 3.62% for Basic SPN, by 6.10% for Enhanced SPN, by 4.61% for Phase SPN and by 6.68% for MLE SPN. It was closely followed by SQI which degraded the sensor identification accuracy by 1.39% for Basic SPN, by 2.05% for Enhanced SPN, by 0.42% for Phase SPN and by 3.10% for MLE SPN. Based on the results of this work, it is evident that some illumination normalization schemes which help in improving iris and periocular recognition performance, can negatively impact the performance of sensor identification algorithms.

- **Observation#5**: Gamma transformation and MSR marginally improve the performance of PRNU estimation schemes, as observed when the difference-in-performance values enclosed in parentheses are averaged across the 4 PRNU estimation schemes.

The results are further visualized from two perspectives. First, CMC curves are presented in Figure 5 which depict the effect of each photometric normalization scheme on the PRNU estimation techniques. Secondly, ROC curves are presented in Figure 6 indicating the degree of robustness of each PRNU estimation algorithm when subjected to different illumination normalization methods. These two curves reinforce the observations made above.

Next, we address the following question: *Is there an explanatory model which can describe the performance of the PRNU estimation schemes in the presence of photometrically transformed images?* The next section utilizes a statistical measure to explain the variations in the performance of the sensor identification algorithms when applied to photomtri-
Fig. 5: CMC curves depicting the effect of different illumination normalization processes on PRNU estimation techniques. (a) Original, (b) CLAHE, (c) Gamma correction, (d) Homomorphic filtering, (e) MSR, (f) SQI, (g) DCT normalization and (h) DoG.

Fig. 6: ROC curves depicting sensor identification performance of photometrically transformed images. (a) Basic SPN, (b) Phase SPN, (c) MLE SPN and (d) Enhanced SPN.

V. EXPLANATORY MODEL

The results in the previous section indicate that PRNU estimation schemes are able to recover sensor information reliably for some illumination normalization schemes, barring DoG filtering and SQI transformation. In this section, we study the probability distribution of pixel intensities, i.e., the normalized histograms of the original image and the photometrically transformed images after being subjected to the wavelet based denoising filter, to provide a principled analysis of the performance of PRNU-based sensor identification algorithms. We hypothesize that the degree of disparity between the histograms of the denoised original images and the denoised transformed images will provide insight into the general performance of PRNU estimation algorithms on photometrically modified images. The four sensor identification schemes used in this work are not applied to the raw images directly; rather, the images (both original and transformed) are first subjected to wavelet based denoising, followed by PRNU estimation in the wavelet domain. Thus, it is necessary to consider the denoised images, instead of the raw images, to develop a suitable explanatory model. To this end, we employed the Jensen-Shannon (JS) divergence to compute the dissimilarity between denoised image histograms corresponding to the original image and the photometrically modified image. JS divergence is a symmetric and smoothed version of Kullback-Liebler divergence and yields a finite value [48]. Given two probability distributions, $P_i$ and $P_t$, the JS divergence is computed as follows, $JS(P_\|P_t) = H\left(\frac{1}{2}P_o + \frac{1}{2}P_t\right) - \left(\frac{1}{2}H(P_o) + \frac{1}{2}H(P_t)\right)$. Here, $H$ indicates the Shannon entropy measure corresponding to a random variable, say $X$, and is computed as $H(X) = -\sum_i p_i \log_2(p_i)$. Here, $p_i = P[X = x_i]$. The JS measure is bounded between 0 and 1 (0 corresponds to identical distributions and 1 indicates high dissimilarity). Thus, JS divergence computes the average entropy of the two distributions: higher the entropy value, the more dissimilar are the two distributions.
First, we generated the probability distributions (i.e., the normalized histograms) of the denoised original and denoised transformed images. Next, we computed the JS divergence between the two probability distributions. Finally, the JS values corresponding to all the images were averaged to compute a single JS measure value for a given sensor. Table III reports the JS divergence pertaining to different transformations for each of the 11 sensors. The average and standard deviation of the JS values corresponding to the 11 sensors are computed for each of the photometric transformations. The highest divergence value corresponding to a particular transformation is bolded, while the lowest divergence value is italicized. Some important observations from Table III are summarized below.

- **Observation#1**: Gamma transformation resulted in the least JS divergence value. It indicates that the normalized histograms of denoised original and Gamma transformed images are highly similar. So it is not surprising that Gamma transformation resulted in only a marginal degradation (for Enhanced SPN) in sensor identification accuracy as evident from the fourth row in Table III.

- **Observation#2**: 7 out of 11 sensors reported maximum divergence values for the SQI transformation, which resulted in the second worst degradation in Rank 1 accuracy (note the last row in Table III), trailing just behind DoG.

- **Observation#3**: The overall results indicate that pixel intensity distributions of the wavelet denoised images have an important role to play with regards to PRNU.

In summary, Enhanced SPN and MLE SPN are robust to most of the illumination normalization schemes considered in this work. Both these methods use $L^2$—normalization of noise residuals to account for the variations arising due to constructive differences of sensors [13], which possibly facilitates a more accurate PRNU estimation. Gamma correction and MSR can be used for ocular image enhancement without impairing the performance of the sensor identification module. SQI and DoG filtering, on the other hand, degrade the performance of sensor identification algorithms.

**VI. Summary and Future Work**

This work investigated the impact of photometric transformations on PRNU estimation schemes and employed an explanatory model to understand their performance in the presence of photometrically modified images. Iris and peri-ocular recognition systems typically use illumination normalization to enhance ocular images. In this work, photometric transformations which are known to positively impact ocular recognition have been considered for experimental analysis. Experiments involving 7 ocular enhancement schemes and 4 PRNU estimation schemes indicate that Enhanced SPN and MLE SPN are robust to a majority of the illumination normalization schemes considered in this work, and that DoG filtering and SQI are detrimental for sensor identification (see Section IV-B). The explanatory model indicates that those photometric transformations causing significant deviation of the distribution pertaining to the denoised photometrically modified image from that of the denoised original image can negatively impact sensor identification performance. The relative dissimilarity between the distributions pertaining to the denoised original and photometrically transformed images was quantified using the Jensen-Shannon divergence which explained sensor identification performance in presence of photometric transformations.

Future work will focus on determining if multiple PRNU estimation schemes can be combined to generate a robust sensor identification scheme that can successfully work on diverse images. Further, methods to detect deliberately perturbed PRNU noise patterns [49] will be developed. In the current work, 11 ocular datasets corresponding to 11 different sensor brands were utilized. Similar experiments involving different devices corresponding to the same sensor brand need to be conducted. Finally, effective fusion schemes for combining iris recognition with device recognition will be designed to perform reliable person authentication in devices such as mobile phones.

**Acknowledgement**

Images in Figure 3 are taken from the following websites.


**References**


[34] V. Struc and N. Pavesic, “Photometric normalization techniques for illumination invariance,” in Advances in Face Image Analysis: Techniques and Technologies, Y. Zhang, Ed. IGI-Global, 01 2011, pp. 279–300.


