ANALYSIS OF DENOISING FILTERS FOR PHOTO RESPONSE NON UNIFORMITY NOISE EXTRACTION IN SOURCE CAMERA IDENTIFICATION

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ABSTRACT

Identification of the source that has generated a digital content is considered one of the main open issues in multimedia forensics community. The extraction of photo-response non-uniformity (PRNU) noise has been so far indicated as a mean to identify sensor fingerprint. Such a fingerprint can be estimated from multiple images taken by the same camera by means of a denoising filtering operation. This paper presents an analysis of the performances of different denoising filters based on diverse noise models when applied for digital camera tracking. In particular, a digital filter, based on a signal-dependent noise model, is introduced and compared with others commonly adopted for this purpose. A theoretical framework and experimental results are provided and discussed.

***Index Terms*—** Digital forensics, source camera identification, photo response non uniformity, wavelet denoising filter

1. INTRODUCTION

Digital forensics science emerged in the last decade in response to the escalation of crimes committed by the use of electronic devices as an instrument used to commit a crime or as a repository of evidences related to a crime (e.g. piracy and child-pornography). For instance a digital camera could be the instrument used to commit a crime and/or a digital photograph, being the evidence related to an illegal action, might have been altered to mislead the judgement. One important element of digital forensics is the credibility of the digital evidence in order to assess digital data origin and authenticity. In this paper digital images are taken in account focusing on evaluating image origin determining the specific digital camera which has acquired that content. It is possible to split the source identification problem in two fields [1]: the first is devoted to determine the specific digital camera or scanner and also identify the model and brand that acquired an image [6, 3, 2, 7], the second one is dedicated to investigate the kind of device [4, 5] that has generated the image under examination (digital camera, scanner, computer graphics images). Various solutions have been proposed in literature to solve the source identification problem analyzing the digital device acquisition process in order to find a fingerprint left by the device like the use of Color Filter Array (CFA) characteristics [7, 6] and the Photo Response Non-Uniformity (PRNU) noise [4, 5, 3, 2]. The PRNU noise is induced by intrinsic inhomogeneities over the silicon wafer and imperfections generated during sensor manufacturing process of CCD/CMOSs. The PRNU is used as sensor fingerprint and it is commonly employed to solve the problem of digital camera sensor identification. Such a technique is investigated in this paper. The extraction of PRNU noise happens through a digital filtering operation from a set of digital images taken by a camera. After that, the PRNU noise of the to-be-checked image is extracted and compared with the available fingerprints and then the image is classified as taken (or not) by a certain camera. It is important to point out, for the further discussion, that the PRNU noise is deterministically embedded in each image the sensor acquired.

In this paper we present a theoretical and experimental comparative analysis of different wavelet denoising filters to estimate the PRNU in order to solve the digital camera identification problem. We have used two denoising filters operating in the wavelet domain and based on different noise models. The first is the filter proposed in [8] and used in [3] and the second filter is a MMSE filter operating in the undecimated wavelet domain [10]. Introducing this kind of filter we make an assumption that the digital camera noise is considered as dependent on the sensed signal, while using the filter described in [8] a signal-independent noise model is supposed.

The filter in [10] is used for the first time in the digital forensic domain to solve the problem of source camera identification, generally it is adopted for speckle and film-grain noise removal in coherent radiation imaging systems including ultrasound, infrared and laser imaging and synthetic aperture radar (SAR).

The paper layout is the following: in Section 2 the two denoising filters are introduced, in Section 3 we describe the digital camera sensor output model that will be used to derive the estimation of PRNU and the noise models for the two filters will be discussed. Some experimental results are presented to evaluate the denoising filters performances in Section 4; finally in Section 5 conclusions are drawn.

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2. DENOISING FILTERS

According to PRNU methodology, it is crucial to analyze the type of denoising filter to be used for the extraction of such a noise. In this work we have decided to evaluate two denoising filters described in detail hereafter: a spatially adaptive statistical modelling of wavelet coefficients filter [8] (Mihcak's Filter) and a MMSE filter operating in the undecimated wavelet domain [10] (Argenti's Filter). The first one adopts a simple additive noise model, on the contrary the second one is based on a signal dependent noise model.

For sake of completeness a simple low-pass filter in the wavelets domain (LP Filter) has been considered too, to provide a performance lower bound during the experimental tests. In this case, after a 4 level Discrete Wavelets Transform (DWT), all the detail coefficients are set to zero and the Inverse Discrete Wavelets Transform (IDWT) is performed to reconstruct the denoised image. The extreme simplicity of this filter is inversely proportional to its accuracy, because setting to zero the coefficients of detail equally removes noise and details that are part of the content of the image. Therefore, the results obtained when we used this filter are presumably coarser.

2.1. Mihcak's Filter [8]

This filter is based on a spatially adaptive statistical modelling of wavelet coefficients; such noisy coefficients $G(k)$ are considered as the addition of the noise-free image $X(k)$ (a locally stationary i.i.d. signal with zero mean) and the noise component $n(k)$ (a stationary white Gaussian noise with known variance σ_n^2). The target is to retrieve the original image coefficients as well as possible from the noisy observation. By using a local Wiener filter (Equation (1)) we obtain an estimate of the denoised image in the wavelet domain and then apply the IDWT (Inverse DWT).

$$\hat{X}(k) = \frac{\sigma_x^2(k)}{\sigma_x^2(k) + \sigma_n^2} G(k) \tag{1}$$

However, we can not use the true signal variance $\sigma_x^2(k)$ since it is unknown, but only an estimate $\hat{\sigma}_x^2(k)$ achieved by previously using a MAP (Maximum A-posteriori Probability) approach on noisy wavelet coefficients.

2.2. Argenti's Filter [10]

Unlike the filter seen before this filter is based on a signal-dependent noise model (see Equation 2):

$$\mathbf{I} = \mathbf{I}_o + [\mathbf{I}_o]^\alpha \cdot \mathbf{U} + \mathbf{W}, \tag{2}$$

where $\mathbf{I}$ and $\mathbf{I}_o$ represent the noisy and noise-free images respectively, while $\mathbf{U}$ states for a stationary zero-mean uncorrelated random process independent of $\mathbf{I}_o$ and $\mathbf{W}$ takes into account of electronics noise (zero-mean white and gaussian). The term α is the exponent that rules the dependence of noise from the signal. It is a parametric model which meets different situations of acquisition [11]. The parameters to be estimated are: α, σ_U^2 which is the variance of $\mathbf{U}$ and σ_W^2 which is the variance of electronic noise $\mathbf{W}$, that can simply be estimated from black image area. The denoising method is based on MMSE filtering in undecimated wavelet domain: after the estimation of the parameters α and σ_U^2 in the spatial domain, the undecimated wavelet transform of the image is computed and then a MMSE filtering in this domain is applied according to the supplied parameters. IDWT to reconstruct the estimated noise-free image is finally performed.

2.2.1. *The estimation of α and σ_U*

As described above two are the parameters to be estimated in the noise model (Equation (2)): α and σ_U^2. In [9] has been proposed an iterative algorithm to estimate these parameters which utilizes an adaptive filter (a MMSE noise filter in the spatial domain). After simple calculation [9], it is possible to derive the relationship among $\tilde{\sigma}_I$, the image $\mathbf{I}$ and σ_U expressed in Equation (3) which is valid on homogeneous pixels:

$$\log[\tilde{\sigma}_{\mathbf{I}}] = \alpha \cdot \log\{E[\mathbf{I}]\} + \log(\sigma_u). \tag{3}$$

So on homogeneous pixels, the ensemble statistics of $\mathbf{I}$ are aligned along a straight line having α as a slope and $\log(\sigma_U)$ as intercept. At each step of the algorithm, the α and σ_U estimate are substituted in the MMSE spatial filter in order to obtain the noise free image on which the homogeneous pixels are selected through an homogeneity equation described in detail in [9]. On these homogeneous pixels a log scatter plot is computed, the regression line is estimated and then the α and σ_U are found.

3. DIGITAL CAMERA SENSOR OUTPUT MODEL

Digital camera acquisition process is well-known as being composed by different processes such as signal quantization, white balance, color and gamma correction, filtering and usually JPEG compression. This variety of effects, together with the diversities due to the specific kind of camera, determine that a precise modelling is difficult to be achieved. In [3] a quite complete model, which takes into account most of the components relevant for forensic task, is introduced. Such a model is reported in Equation (4), where $\mathbf{I}$ is the 2-D sensor output (noisy image), g and γ are the gain factor and the gamma correction respectively, and $\mathbf{Y}$ is the 2-D incident light:

$$\mathbf{I} = g^\gamma \cdot [(1 + \mathbf{K})\mathbf{Y} + \mathbf{\Lambda}]^\gamma + \mathbf{\Theta_q}. \tag{4}$$

The term that is useful for the forensic analysis is $\mathbf{K}$ which represents a zero-mean noise-like signal that is the PRNU

(Photo Response Non-Uniformity) (i.e. the 2-D sensor fingerprint deterministically superimposed to each taken digital image), while $\mathbf{\Theta_q}$ is the quantization noise and $\mathbf{\Lambda}$ takes into account a combination of different noise sources.

According to the discussion presented in [3], this expression can be simplified to get to a more concise representation (see Equation (5)), where $\mathbf{I}_o$ is the noise-free sensor output, $\mathbf{K}_1 = \mathbf{K} \cdot \gamma$ is basically considered again as the PRNU and $\mathbf{\Theta}$ is an ensemble of independent random noise components.

$$\mathbf{I} = \mathbf{I}_o + \mathbf{I}_o \cdot \mathbf{K}_1 + \mathbf{\Theta} \quad (5)$$

This expression points out an additive-multiplicative relation between the signal without noise and the noise terms. An estimate $\hat{\mathbf{I}}_o = F_M(\mathbf{I})$ of the denoised image $\mathbf{I}_o$ is usually obtained by a wavelet-based denoising filter F_M [8], though such a filter is built on an additive noise model as explained in Section 2.1. It is immediate to comprehend that Equation (2) coincides with Equation (5) ($\mathbf{U}$ and $\mathbf{W}$ are the same of $\mathbf{K_1}$ and of $\mathbf{\Theta}$ respectively) except for the term α ($|\alpha| \leq 1$) which determines signal-dependency. When α is equal to 1 for purely multiplicative noise the two models are identical. On the basis of this consideration, it is interesting to analyze how this difference in modelling can influence filtering and consequently PRNU detection.

The two digital filters F_M and F_A will yield two estimates $F_M(\mathbf{I})$ and $F_A(\mathbf{I})$, and when are tested against signal-dependent generated noisy images, results achieved in denoising operation are generally superior with F_A filter (e.g. 2 or 3 dB of PSNR improvement), as expected. This witnesses the goodness of the Argenti's filter when the noise model is exactly matched.

When the noise-free image is obtained, the PRNU noise is computed, at least in a rough approach, by subtracting from the noisy image the denoised one. The more accurate the denoised image estimate, the more reliable the fingerprint extraction so high relevence is given to the kind denoising filter used. The sensor fingerprint $\mathbf{N}$ is obtained, as indicated in Equation (6), by suppressing the scene content:

$$\mathbf{N} = \mathbf{I} - \hat{\mathbf{I}}_o. \quad (6)$$

Successively a refinement of the fingerprint is carried out by averaging the results got over a set of M training images (usually M is around 50). This operation yields to delete different noise components that are present on the acquired images but which are not systematic like PRNU.

4. EXPERIMENTAL RESULTS

In the first part of this section the denoising filters performances are discussed in relation with the digital camera identification. In the second part of this section experimental measures of the model parameters associated to the Argenti's filter are reported and analyzed.

4.1. Denoising filters performances

In this section experimental results for digital camera identification, carried out to compare the three filters (LP, Mihcak and Argenti) used to estimate the PRNU noise are collected and analyzed. The data set is composed by images coming from 10 digital cameras of various brand and model taken by generic users in different kinds of settings. We have created the fingerprint for each camera in the data set, averaging residual noises from 40 images; the remaining photos have composed the test-set (approximately 250 images for each camera). For each camera we obtained three fingerprints, one for each denoising filter under investigation. The correlation between each fingeprint and the residual noises of the test images is performed. In Table 1 a numerical example of the correlation values for a selection of images from a Concord 2000 is shown. Each fingerprint calculated for the Nikon E4600, Samsung MS11 etc., through the three filters under examination (Low Pass, Mihcak and Argenti) is compared with the residual noise of a selection of Concord 2000 test images (from 30 to 38). It is worth to point out that the correlation values in the last column of the Table 1 have the higher values, so the images taken by the Concord 2000 are correctly identified as belonging to Concord 2000 digital camera. Moreover it is interesting to observe that higher values of the last column are encountered when the correlation is made between the fingerprint and the PRNU noise residual calculated with the Argenti filter (see the lower part of the Table 1).

To decide if an image has been acquired or not by a specific camera we introduced a statistical threshold for the correlation value. To calculate the threshold we used the Neyman-Pearson approach based on two parameters: the False Acceptance Ratio (FAR) and False Rejection Ratio (FRR).

The FAR establishes a limit to the number of cases in which an image is wrongly identified as related to a given fingerprint. The FRR is the rate that indicates the number of images that, though related to the given fingerprint, are not recognized as such. With this method we set an *a priori* FAR and we found the threshold that minimize FRR. We suppose that the distribution of the correlation between the fingerprint of the camera C_0 and the noise residuals coming from images taken by different cameras is Generalized Gaussian (see Equation (7)).

$$f(x;\delta,\beta,\mu) = \frac{1}{2\delta\Gamma(1+1/\beta)} e^{-(\frac{|x-\mu|}{\delta})^{\beta}} \quad (7)$$

In Figure 1 the distribution of correlation between the Nikon D40x with noise residual from a selection of images taken by the others cameras in the database (except the Nikon D40x) is shown. It is possible to fit the data with a Generalized Gaussian distribution centered close to zero. Furthermore, the standard deviation is bigger in the Low Pass filter case and decrease in the other two filters. So it's possible to consider the standard deviation as a performance marker of

Filter Type	n.	Nikon E4600	Samsung MS11	Olympus FE120	Sony S650	Nikon L12	**Concord 2000**
Low Pass	30	-1.714	0.735	-0.234	0.778	0.262	**67.969**
	31	0.083	-0.160	0.469	-0.056	-0.265	**83.186**
	32	-1.007	0.593	-0.254	0.090	0.147	**67.926**
	33	-0.722	-0.522	0.411	-0.158	-0.456	**39.619**
	34	-1.815	0.700	0.322	0.883	1.037	**43.593**
	35	0.613	-1.261	-0.028	-0.340	-0.444	**68.18**
	36	-0.280	0.292	-0.539	0.294	-0.229	**69.173**
	37	0.477	0.016	0.347	-0.082	0.341	**99.602**
	38	0.416	-0.013	-0.001	-0.239	0.481	**63.028**
Mihcak	30	1.210	-0.487	0.365	0.173	-1.997	**101.070**
	31	-0.370	-1.152	0.263	-0.880	-1.157	**98.416**
	32	0.190	0.923	0.171	0.619	0.043	**100.710**
	33	-1.486	1.226	-0.524	0.595	0.026	**74.502**
	34	1.154	-0.621	0.031	1.368	0.449	**70.787**
	35	0.288	-0.594	0.917	-0.645	0.440	**105.400**
	36	0.166	0.470	-0.736	0.001	-0.064	**102.320**
	37	0.219	0.946	-0.048	0.185	0.736	**145.380**
	38	0.525	0.948	-0.282	0.679	0.996	**92.319**
Argenti	30	0.884	-0.469	0.026	0.334	-0.471	**111.530**
	31	-3.362	-4.128	3.466	-1.883	-1.879	**111.290**
	32	0.046	1.355	-1.608	1.026	0.787	**102.050**
	33	-0.591	-0.238	-0.547	-0.162	-0.959	**84.691**
	34	1.292	-0.762	-0.549	-1.179	-0.720	**79.884**
	35	0.174	-0.423	0.252	-0.421	-0.577	**113.380**
	36	-0.046	-1.253	-0.212	-1.235	-0.060	**105.320**
	37	1.291	0.051	-0.839	1.217	-0.629	**143.020**
	38	1.556	0.216	-1.395	0.889	1.211	**96.836**

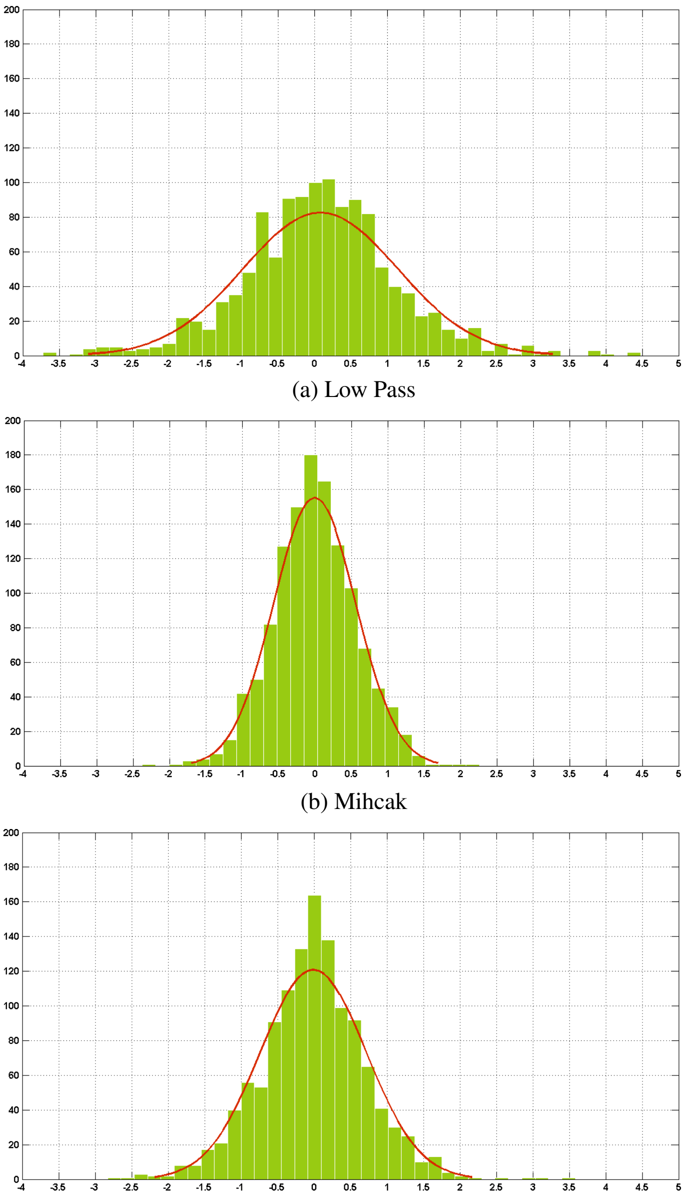
Table 1. Correlation values (values are to be scaled by 10^{-3}) for a selection of 9 test images (30 to 38) from a Concord 2000 digital camera calculated with the fingerprints of 6 cameras (Concord 2000 included).

	LP		Mihcak		Argenti	
Camera	t (10^{-3})	FRR	t (10^{-3})	FRR	t (10^{-3})	FRR
Nikon E4600	3.0	3x10^{-2}	3.0	8.11x10^{-3}	9.3	8.11x10^{-3}
Samsung MS11	15.5	2x10^{-2}	4.6	1.8x10^{-10}	9.9	8x10^{-12}
Olympus FE120	4.2	2.8x10^{-2}	2.6	1.2x10^{-2}	9.9	8x10^{-4}
Sony S650	4.9	2.6x10^{-2}	2.0	3.1x10^{-3}	7.7	1.8x10^{-2}
Nikon L12	5.6	1.18$10^{-1}$	4.1	8.8x10^{-3}	8.4	9.4x10^{-3}
Canon DI50	5.7	5.2$10^{-1}$	4.2	4.5x10^{-2}	7.7	4.7x10^{-2}
Nikon D40x	2.1	1.76$10^{-1}$	2.4	7x10^{-3}	4.8	1.5x10^{-2}
Canon Diiz	7.7	2.72$10^{-1}$	4.5	9.3x10^{-2}	5.2	5.7x10^{-2}
HP PSC935	4.6	4.5$10^{-1}$	4.1	1.9x10^{-10}	5.0	7x10^{-2}
Concord 2000	3.3	1.3x10^{-2}	3.7	5x10^{-4}	5.8	9x10^{-4}

Table 2. Thresholds t and FRR for all 10 cameras with a FAR=10^{-3} for the three different denoising filters.

the three filter, and it is possible to presume that Argenti's and Mihcak's filter will show better results. The method of moments [2] is used to estimate the parameters of Equation (7) and then we calculate the cumulative density function of $f(x;\delta,\beta,\mu)$ over all the cameras at disposal, except C_0. By using the Neyman-Pearson approach we determine the threshold by minimizing the probability of rejection, given an upper bound on the FAR = 10^{-3}. In Table 2 the decision thresholds and the FRR computed for each denoising filter relatively to the 10 test cameras are shown.

The LP filter has the worst behavior as obviously expected. The other two filters showed a comparable behavior; in fact

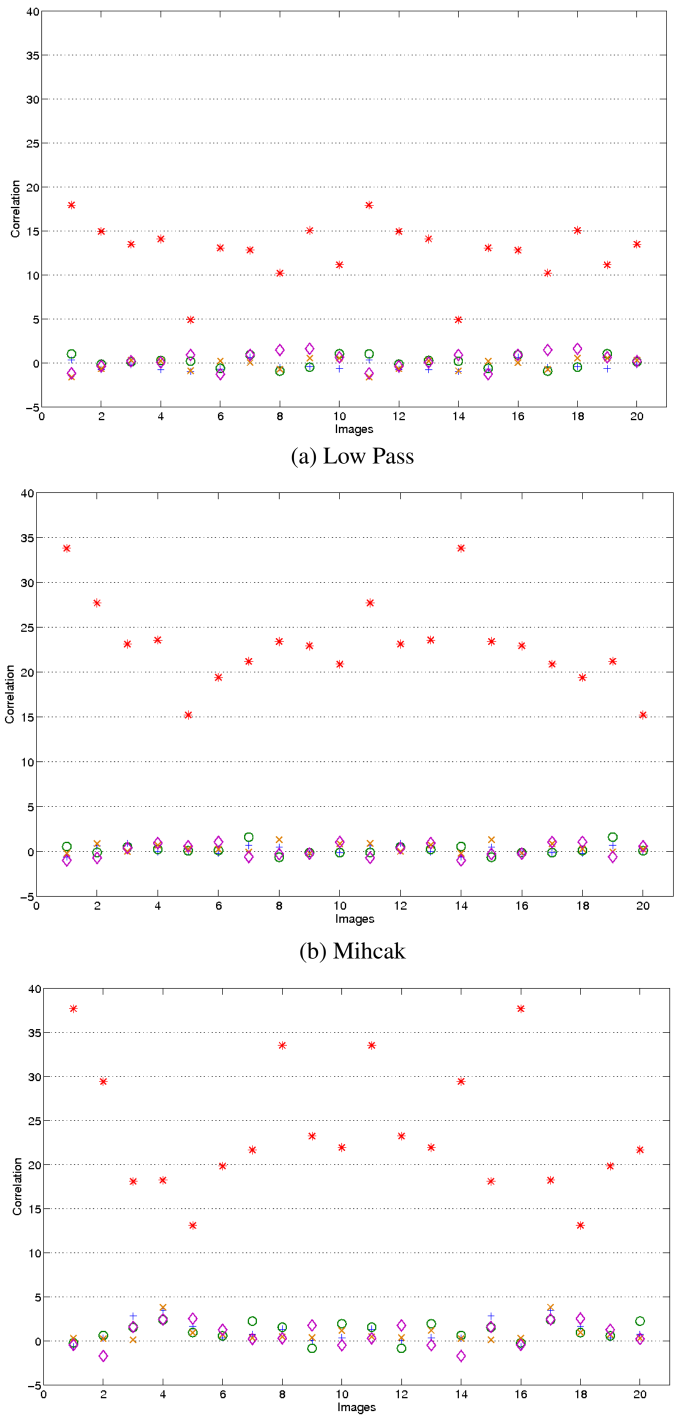


(a) Low Pass

(b) Mihcak

(c) Argenti

Fig. 1. Distribution of the correlation values between Nikon D40x fingerprint with residual noises taken by a random selection of 300 images belonging to different cameras. The continuous line is the Generalized Gaussian fitting.



(a) Low Pass

(b) Mihcak

(c) Argenti

Fig. 2. Correlation values of residual noises (values are to be scaled by 10^{-3}) of 20 images coming from an Olympus FE120 with 5 fingerprints. Legend: $+$ Nikon E4600, $\circ$ Samsung MS11, $*$ Olympus FE120, $\times$ Sony S650, $\diamond$ Nikon L12

in most cases the value of FRR has the same order of magnitude though Argenti's filter has a significative lower FRR for Samsung MS11 and Olympus FE120. However Argenti's filter does not exhibit a considerable improvement in the results of camera identification compared to Mihcak's filter. According to our analysis, this is mainly due to the sensibility of the filter itself to the reliability of the parameters estimation (see Section 4.2). In fact we noted, by acting on noisy images generated by introducing a speckle noise, that filter performances drastically decreased, when an uncorrect estimation was done, specifically for the parameter α.

In Figure 2 the correlation values for images from a Olympus FE120 with 5 fingerprints of various cameras are pictured. The distributions of the correlation values in all the three cases are always well separated; in fact the higher values are those related to the correlation between the noise residual of the Olympus FE120 images and its fingerprint. In the Mihcak and Argenti filter cases (Figure 2 (b),(c)) the two classes are better clustered than in Figure 2 (a). This result confirms that using a denoising filter adequate at the noise model there is an improvement in the performance of the camera identification method.

4.2. Consideration about α and σ_U estimate in the Argenti's filter

The Argenti's filter proposes, as said in Section 2.2.1, an iterative estimate of α and σ_U in the parametric noise model (Equation (2)). So some tests to check the reliability of such estimation have been performed. We consider a noise free computer generated image (Figure 3), then we corrupted this image with a noise in order to achieve a $SNR = 3dB$, driven by the parameters α and σ_U. Then using the estimation algorithm proposed in 2.2.1 we obtained the $\hat{\alpha}$ and $\hat{\sigma_U}$ estimated values. In Table 3 the results of this test are listed: in the first and the second columns there are the actual α and σ_U values while in the third and the forth there are the corresponding estimated values obtained by implementing the algorithm proposed in [9]. In general the estimate of each couple of value (α, σ_U) seems to be consistent with the real ones.

α	σ_U	$\hat{\alpha}$	$\hat{\sigma_U}$
-0.80	1340.66	-0.77	1187.47
-0.70	885.20	-0.66	751.36
-0.60	578.87	-0.55	461.65
-0.50	375.11	-0.45	298.65
-0.40	241.01	-0.35	188.70
-0.30	153.63	-0.25	121.34
-0.20	97.22	-0.16	80.27
-0.10	61.12	-0.08	54.00
0.00	38.19	0.01	36.31
0.10	23.74	0.09	24.70
0.20	14.68	0.17	16.78
0.30	9.04	0.24	11.67
0.40	5.55	0.32	7.84
0.50	3.39	0.40	5.35
0.60	2.07	0.48	3.57
0.70	1.25	0.57	2.36
0.80	0.76	0.65	1.54

Table 3. The real α and σ_U and their estimate $\hat{\alpha}$ and $\hat{\sigma_U}$ over different measures.

Furthermore we considered the estimate of these parameters in relation to the correlation value obtained from the fingerprint and the residual noise when the Argenti's denoising filter is used. We calculated the first estimate (α^1 and σ_U^1) of the parameters for each photo taken by a certain camera C.

Fig. 3. A computer graphics image *"Room"*.

We computed new α and σ_U values calculated in the range of [-50%, +50%] from the initial value (121 values are considered in total). Then we calculated the residual noises for each of the 121 couples and then the correlation of them with the fingerprint of the camera C is measured. In the majority of the observed cases the correlation value does not improve using the 121 values of α and σ_U instead the initial one. In Figure 4 an example of this situation for Nikon E4600 is presented. The values of (α, σ_U) in the (x, y) axes, and in z axes the value of the correlation are reported. The higher value of correlation is in the central point of the graph ($x = 0$, $y = 0$) that corresponds at the initial estimate of the two parameters. According to these observations we used the first estimate of the α and σ_U parameters for the computation of the PRNU noise. So it is necessary to find a new technique to estimate α and σ_U parameters in order to improve their reliability.

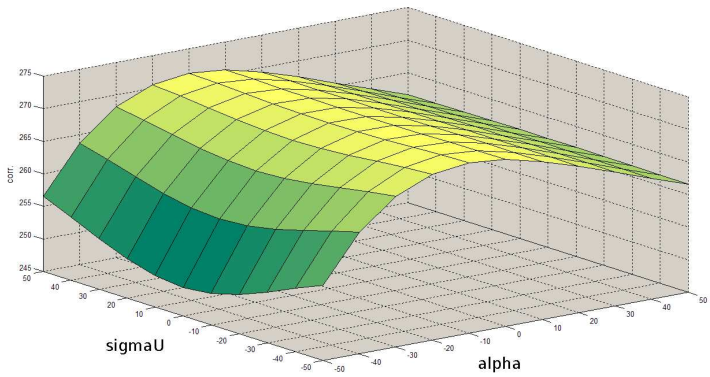


Fig. 4. Trend of the correlation values with respect to (α, σ_U) for a Nikon E4600.

5. CONCLUSIONS

In this paper, we have analyzed how different denoising filters based on diverse noise models can be adopted for PRNU extraction in source camera identification. In particular, experimental results have demonstrated that when the noise model exactly matches the actual situation (i.e digital image acquisition process), the filter based on such a model grants better performances if the parameters, needed for filtering, are reliably estimated (e.g. Argenti's filter). This is an input in proceeding to research appropriate solutions which can permit a better PRNU detection. Future works will be dedicated to deeply investigate how parameters estimate really affects the successive filtering operation and furthermore to study a more effective methodology for PRNU extraction instead of that roughly adopted in Equation (6) by properly taking into account all the other. Other tests will be performed for the source identification, in the case of digital cameras of the same brand and model to better understand the both filters behaviour.

6. REFERENCES

[1] Tran Van Lanh, Kai-Sen Chong, S. Emmanuel and M.S. Kankanhalli, "A Survey on Digital Camera Image Forensic Methods," *IEEE International Conference on Multimedia and Expo*, vol., no., pp.16-19, 2007.

[2] J. Lukas, J. Fridrich and M. Goljan, "Digital Camera Identification from Sensor Pattern Noise," *IEEE Trans. on Information Forensics and Security*, vol. 1(2), pp. 205-214, 2006.

[3] M. Chen, J. Fridrich, M. Goljan and J. Lukas, "Determining Image Origin and Integrity Using Sensor Noise," *IEEE Trans. on Information Forensics and Security*, vol. 3(1), pp. 74-90, 2008.

[4] R. Caldelli, I. Amerini and F. Picchioni, "Distinguishing between camera and scanned images by means of frequency analysis," *Proceedings of e-Forensics*, 2009.

[5] N. Khanna, G.T.-C. Chiu, J. P. Allebach and E. J. Delp, "Forensic techniques for classifying scanner, computer generated and digital camera images," *Proc. IEEE ICASSP*, 2008.

[6] S. Bayram, H. T. Sencar and N. Memon, "Source Camera Identification Based on CFA Interpolation," *Proc. of IEEE ICIP*, 2005.

[7] A. Swaminathan, M. Wu and K.J.R. Liu, "Digital Image Forensics via Intrinsic Fingerprints," *IEEE Transactions on Information Forensics and Security*, vol.3, no.1, pp.101-117, 2008.

[8] M.K. Mihcak, I. Kozintsev and K. Ramchandran, "Spatially Adaptive Statistical Modeling of Wavelet Image Coefficients and its Application to Denoising," *Proc. IEEE ICASSP*, vol. 6, pp. 3253-3256, 1999.

[9] G. Torricelli, F. Argenti, and L. Alparone, "Modelling and assessment of signal-dependent noise for image denoising," *Proc. EUSIPCO*, pp.287-290, 2002.

[10] L. Alparone, F. Argenti and G. Torricelli, "MMSE filtering of generalised signal-dependent noise in spatial and shift-invariant wavelet domain," *Signal Process Journal*, Vol. 86, no. 8, pp. 2056-2066, 2006.

[11] A.K. Jain, "Fundamentals of Digital Image Processing," Prentice Hall, Engl. Cliffs, NJ, 1989.