Source Camera Identification using Non-decimated Wavelet Transform

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Abstract. Source Camera identification of digital images can be performed by matching the sensor pattern noise (SPN) of the images with that of the camera reference signature. This paper presents a non-decimated wavelet based source camera identification method for digital images. The proposed algorithm applies a non-decimated wavelet transform on the input image and split the image into its wavelet sub-bands. The coefficients within the resulting wavelet high frequency sub-bands are filtered to extract the SPN of the image. Cross correlation of the image SPN and the camera reference SPN signature is then used to identify the most likely source device of the image. Experimental results were generated using images of ten cameras to identify the source camera of the images. Results show that the proposed technique generates superior results to that of the state of the art wavelet based source camera identification.

Keywords: Sensor Pattern Noise · Non-decimated Wavelet Transform · Source Identification · PRNU · Digital Forensics · SPN

1 Introduction

With the decrease in cost of digital cameras, cell phones and tablets with cameras, the proliferation of digital photographs has reached epic proportions. Some of these imaging devices and the photographs that they produce are used in the commission of crime. A method to link the digital images, recovered by law enforcement agencies, to the source imaging device that created these photographs would be helpful in linking suspects to crimes. Within the digital camera image creation pipeline, described in [1], artifacts are left in the created image at each processing stage. These artifacts can be from processing inside the device or characteristics of the device itself [2] and can be extracted as features from images in order to link to the source imaging device. Some of the artifacts from the camera pipeline that can be used for source device identification are demosaicing algorithm of Color Filter Array (CFA), quantization tables for JPEG image compression, EXIF header of JPEG image, lens aberration and sensor noise. The first three techniques can identify the make and/or model of the source device whereas the last two techniques can identify a specific source device.

adfa, p. 1, 2011.

Within the scope of this paper, we will concentrate on sensor noise to identify the source device. The sensor noise, so-called sensor pattern noise (SPN), is a deterministic artifact left in any image created by an imaging sensor. The SPN consists mainly of the photo response non-uniformity (PRNU) and to a lesser extent the fixed pattern noise (FPN) [3]. The PRNU occurs due to manufacturing imperfections and inhomogeneity in the silicon chips of the charge-coupled device (CCD) or complementary metal oxide semiconductor (CMOS) imaging sensors and the PRNU is unique to an individual sensor. The slight variation in conversion of light energy to electrical energy by each sensor pixel also contributes to the PRNU [4]. The FPN occurs due to dark currents when the sensor is not exposed to light and is eliminated by some cameras. Lukas et al [3] proposed the extraction of SPN as a digital signature to identify the source imaging device and most subsequent extraction methods proposed by other researchers extract the SPN and use its main component PRNU as digital signature. The process for identification consists of creating a reference SPN signature for the camera sensor and matching the reference fingerprint against SPN signatures from suspect digital photographs.

The most common SPN extraction method is performed using wavelet transform in the frequency domain. The SPN, n, is a medium to high frequency signal, which can be separated from the image, I, using a high-pass filter [3]

$$n = I - f(I) \tag{1}$$

where f is denoising function that performs as a low-pass filter to extract the required signal. To the knowledge of the authors, all the wavelet extraction method uses a Wiener filter as the low-pass filter. Some methods based on wavelet SPN extraction have been proposed to improve the underlying SPN signature. Chen et al introduced the maximum likelihood estimator (MLE) for the SPN combined from multiple images [5]. They set the mean of the rows and columns of the SPN signature to zero in order to attenuate the linear pattern. They apply Wiener filtering after performing the Discrete Fourier Transform (DFT) of the SPN signature to remove blockness artifacts. Another method assumes that the strong components in the SPN signature are caused by image scene details and thus attenuates all strong components [6].

There have been other methods of extracting the SPN from photographs. A two dimensional Gaussian filter in the spatial domain can be used by altering the variance of the filter to find a trade-off between the level of scene details and SPN details [7]. A simplified version of the Total Variation based noise removal algorithm has been used to extract the PRNU [8]. Singular Value Decomposition (SVD) was used to extract the PRNU of images by first estimating the PRNU energy of each image and then converting the PRNU to an additive noise to facilitate extraction using the SVD method [9]. Kang et al, proposed an SPN predictor based on context-adaptive interpolation algorithm to suppress the effect of image scene [10].

All the existing wavelet based SPN extraction methods are based on decimated wavelet decomposition, where the details of the decomposition are down sampled. Non-decimated wavelet transform have been applied in edge detection algorithms for iris segmentation [11]. In this paper, an SPN extraction method is introduced based on non-decimated wavelet transform. All the details of the different sub bands are kept during the wavelet decomposition in order to retain more information about the SPN, which is already a weak signal. Experimental results on a mixture of images from digital cameras and camera phones show promising results for identification of imaging source devices. The rest of the paper is organized as follows: in section 2, the proposed SPN extraction method is explained; in Section 3, a description of the experiments conducted together with the results obtained is detailed. Finally, Section 4 concludes the paper.

2 Proposed SPN Extraction Method

Non-decimated wavelet transform keeps all the details of the wavelet sub-bands during the decomposition process, which allows more information to be retained. Whereas decimated wavelet transform performs down sampling of the sub-bands, most often halving the size of the decomposed signal. Figure 1 shows the block diagram of the proposed algorithm applying non-decimated wavelet transform to an input image in order to extract the SPN.

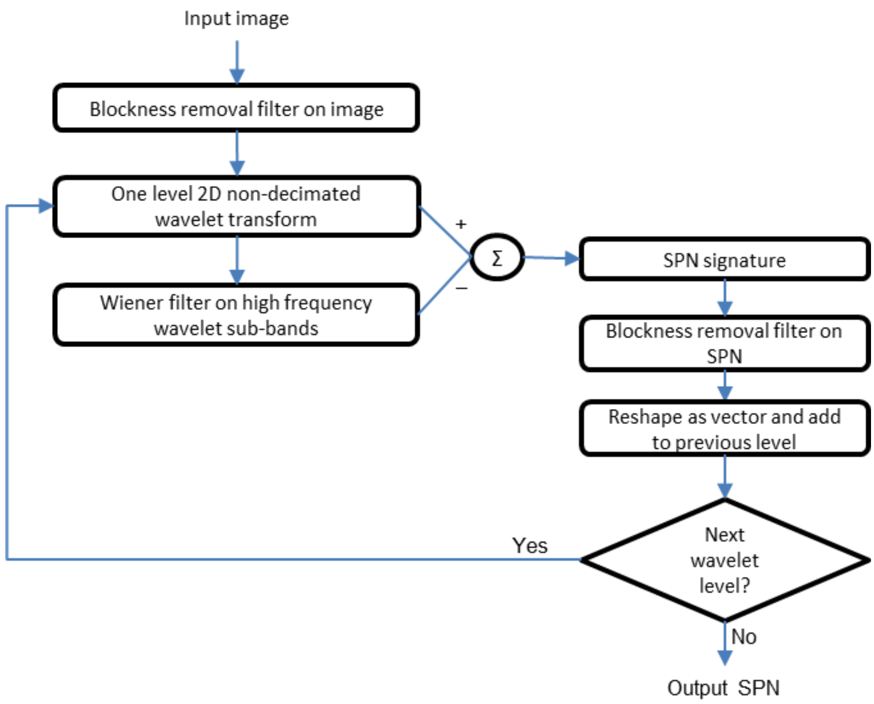

Fig. 1. Block diagram of the proposed SPN extraction algorithm

The algorithm takes an input color image and applies a 2D Wiener filter in the frequency domain by applying DFT (Discrete Fourier Transform). This step is performed to reduce periodical patterns and other artifacts that occur in JPEG images. These patterns are also called blockness artifacts and cause false positives between SPN signatures from different cameras of the same brand or model. A one level non-decimated wavelet transform is applied first on the rows then the columns of the image. The process produces two-dimensional wavelet decomposition where the sub-bands are as shown in Figure 2.

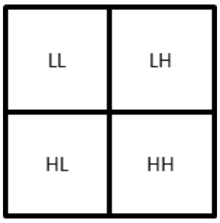

Fig. 2. Two dimensional wavelet sub-bands, where LL is LowLow, LH is LowHigh, HL is HighLow and HH is HighHigh coefficients frequency respectively.

The LL – LowLow, LH – LowHigh, HL – HighLow and HH – HighHigh wavelet sub-bands details represent the High and Low frequencies of the wavelet decomposition of the image. The LL is the approximation details that contain a low frequency representation of the image. The other three sub-bands contain the high frequency coefficients of the wavelet decomposition. The denoising of the three sub-bands of interest is done by applying a low pass filter, in the form of a 2D Wiener filter. The denoising process eliminates all medium to high frequency details from the sub-bands. The SPN signature is obtained by subtracting the low-passed wavelet sub-bands from the original decomposed wavelet sub-bands as shown in equation 1 in the first section of the paper. This process retains only the high frequency details from the non-decimated wavelet decomposition. The SPN extraction stage is performed on the three sub-bands of interest and does not include the approximation details (LL).

Some denoising errors can be introduced in the SPN signature by the denoising filtering process [12]. Most often periodic patterns are formed in the SPN signature. The blockness removal filter is applied to the SPN signature in order to attenuate any blocking artifacts that may have been inserted in the SPN by the denoising function. The SPN is reshaped from a 2D signal to a vector. All the SPN elements are concatenated and form the final SPN signature with information from each level of wavelet decomposition. If another level of wavelet decomposition is required the algorithm will perform the one level 2D non-decimated wavelet decomposition on the approximation details (LL) from the current level decomposition. The level of wavelet decomposition for SPN extraction is passed as a parameter to the algorithm. If the last level of wavelet decomposition has been reached, the output SPN signature is obtained.

3 Experiments and Results

The performance of the proposed source device identification algorithm was assessed by running a set of experiments on an image dataset to test a predefined hypothesis. The results of the algorithm were compared against the state of the art wavelet extraction method.

3.1 Hypothesis and Performance Measure

The identification of a source device using SPN can be formulated as the following binary hypothesis testing:

$$H_0 = \text{Image was not created by camera}$$

$$H_1 = \text{Image was created by camera} \tag{2}$$

where H_0 is the null hypothesis and H_1 is the alternative hypothesis. The correlation match is performed between the camera reference SPN and each individual image SPN in the dataset. If the correlation coefficient is above a predetermined threshold, the null hypothesis can be rejected. The threshold is pre-set empirically to 0.01, and it has been shown in previous research in source device identification that a threshold of 0.01 for the cross correlation coefficient was reasonable [6]. If the null hypothesis is rejected, it can be inferred that the photo originates from the camera fingerprint being tested. If the null hypothesis is not rejected, it can be inferred that the photo does not originate from the camera fingerprint under test.

The results obtained from the proposed scheme were compared against the state of the art in wavelet SPN extraction method [13] and the source code was downloaded from [14]. The experiments were designed so that the SPN extraction methods will be able to identify the source device of an image and that the proposed method can differentiate between devices of the same make and model.

3.2 Experimental Setup

For the purpose of our experiments, a total of 100 images were chosen from 10 imaging devices comprising of digital cameras and camera phones. Each device contributed 10 images. Table 1 shows the list of cameras used, where the camera make and models are listed together with the resolution of the pictures from these devices. The pictures for the digital cameras were selected from the Dresden public image dataset [15]. All cameras that had pictures with the same resolution (3072 x 2304 pixels) were chosen, in order to show that our method could differentiate between cameras that would have similar SPN synchronization pattern. The images from the camera phones were used in the experiments of [9] and they include four phones, with two phones from the same make and model. Furthermore, there are three Canon_Ixus70 cameras in the dataset so that the experiments can further demonstrate the differentiation between camera models. The fact there are three cameras of the same make and model (Canon Ixus70), it was decided to use one of the cameras (*Canon_Ixus70_0*) as the camera reference SPN signature.

Table 1. Cameras used in experiment showing their makes, models and picture resolution

Device Name	Device Type	Make	Model	Picture Resolution (px)
Agfa_DC-733s_0	Digital camera	Agfa	DC-733	3072 x 2304
Canon_Ixus70_0	Digital camera	Canon	Ixus70	3072 x 2304
Canon_Ixus70_1	Digital camera	Canon	Ixus70	3072 x 2304
Canon_Ixus70_2	Digital camera	Canon	Ixus70	3072 x 2304
Rollei_RCP-7325XS_0	Digital camera	Rollei	RCP-7325XS	3072 x 2304
Samsung_L74wide_0	Digital camera	Samsung	L74wide	3072 x 2304
samsung_galaxy_S2_A	Camera Phone	Samsung	Galaxy S2	3262 x 2448
samsung_galaxy_S2_B	Camera Phone	Samsung	Galaxy S2	3262 x 2448
zte_orange_sanfrisco_A	Camera Phone	ZTE	Orange sanfrancisco	1536 x 2048
zte_orange_sanfrisco_B	Camera Phone	ZTE	Orange sanfrancisco	1536 x 2048

To create the camera reference SPN signature, 50 flatfield pictures, pictures of white wall with no scene details, from the *Canon_Ixus70_0* camera were downloaded separately from the natural scene images. The SPN of the 50 images were extracted and averaged into one camera reference SPN. All the 100 images, including the 10 images originating from the *Canon_Ixus70_0* camera was matched against the camrea reference SPN. To ensure generality, the 100 pictures were natural images consisting of a mixture of outdoor and indoor scenes. The Dresden dataset contains natural pictures with similar scenes from different cameras, which ensures that the matching of the SPN is performed in more controlled conditions. To reduce computational complexity, all the images were cropped to a size of 512 x 512 pixels from the centre.

3.3 Results

In order to compare the performance of the proposed algorithm with the state of the art technique, firstly the camera reference SPN of the *Canon_Ixus70_0* camera was created using both algorithms. Secondly, the SPN signatures of the 100 images were extracted using both algorithms and matched against the camera reference SPN. Our proposed method is called ‘non-decimated’ and the state of the art method is called ‘decimated’ in the results section. The results obtained are shown in Figure 3, where the *Canon_Ixus70_0* reference SPN signature and correlated with 100 images from 10 cameras. Images 11 to 20 come from this camera and rest of images from the other 9 cameras. Both non-decimated and decimated correlation coefficient results are displayed. All the images from the *Canon_Ixus70_0* camera were positively matched to the camera reference SPN by rejecting the null hyppthesis, above the threshold of 0.01, when using both methods of extraction as the correlation coefficient values for images 11 to 20 shows in figure 3. The non-decimated method gave higher positive matching results than the decimated method for the 10 images from the

Canon_Ixus70_0 camera. The mean correlation coefficient values for the non-decimated method was 0.0411 and for the decimated method was 0.0407 respectively. The variance in values for images 11 to 20 were 0.00024 and 0.00030 for the non-decimated and decimated methods respectively. The decimated method had more variation in results for positive matchings and the non-decimated method provided more consistent results.

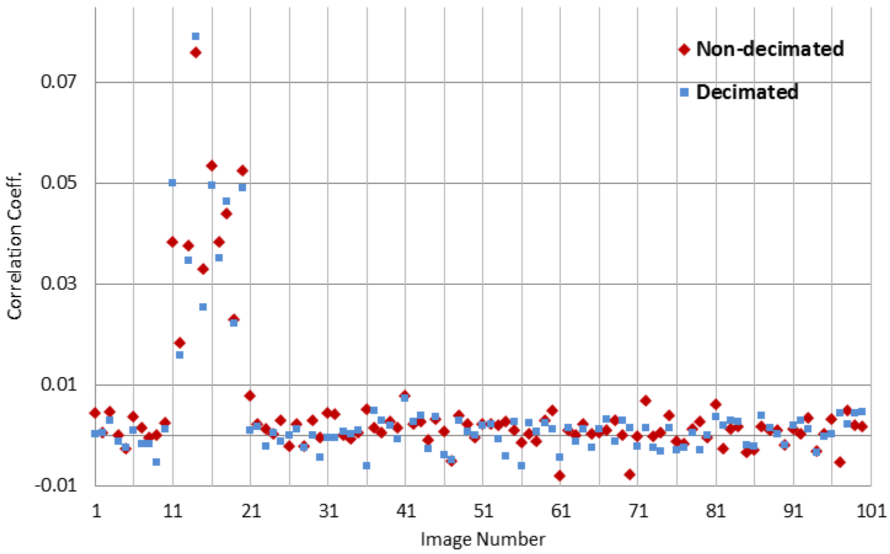

Fig. 3. *Canon_Ixus70_0* reference SPN signature and correlated with 100 images from 10 cameras. Images 11 to 20 come from this camera and rest of images from the other 9 cameras. Both non-decimated and decimated correlation coefficient results are displayed.

The correlation coefficient values for the other two Canon Ixus cameras (*Canon_Ixus70_1*, *Canon_Ixus70_2*), which were images 21 to 30 and 31 to 40 respectively, were close to zero for the non-decimated method similar to the decimated mehod. These results show that our proposed method was able to differentiate between cameras from the same make and model. The correlation coefficient values for the rest of the images from the other 7 cameras were all below the threshold, with no false positive and not rejecting the null hypothesis. The variance in correlation values was 0.00001 for both the non-decimated and decimated methods. Based on the variance of the correlation coefficients obtained it can be seen that the non-decimated method provided a more consistent identification result for the dataset used.

The decimated method can extract the SPN from an image with 4 levels of wavelet decomposition. While performing the experiments with different levels of wavelet decomposition it was found that the non-decimated method managed to extract the SPN signature from an image after the first level of wavelet decomposition. This may be due to the fact that the non-decimated wavelet transform retain more information about the SPN signal, so that it can be extracted after the first level of decomposition.

4 Conclusion

This paper presented a non-decimated wavelet based source camera identification method for digital images. The proposed algorithm applies a non-decimated wavelet transform on the input image and split the image into its wavelet sub-bands. The coefficients within the resulting wavelet high frequency sub-bands are denoised to extract the SPN from the picture. Cross correlation of the image SPN and the camera reference SPN signature was then used to identify the source camera of the image. Experimental results were generated using images of ten cameras to identify the source device of the images. Results showed that the proposed technique generates superior results to that of the state of the art wavelet based source camera identification. A secondary benefit with non-decimated wavelet transform is that the SPN signature can be extracted after the first level of wavelet decomposition as opposed to decimated method where a reliable SPN can only be extracted after 4 levels of wavelet decomposition. Further works to improve the quality of the extracted SPN is underway as well as reduce the dimensionality of the SPN signature.

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