

Source Camera Identification using DWT and Ladct

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Abstract:- Digital image forensics is becoming a crucial area in forensic investigations. There occurs many investigations which need to identify the source of a particular image. Here we discuss about two methods in identification of the source of an image. LADCT and DWT methods which uses the noise residuals from the image to identify and categorize the source of the image. The paper discusses about LADCT and DC method to identify the source and the comparison between the methods to show which method is better in classification of the camera models and also in accuracy of identifying the image.

Keywords:- Ladct, Dct, Prnu, sensor fingerprints, image forensics.

I. INTRODUCTION

As we know technology is growing fast it has changed the photos from old film cameras to digital. Everything has been digitalized and is continuing to digitalizing those which are no yet been digitalized. So the security of the digital data is also an important concern to be noticed. We have so many methods in taking a photo nowadays such as using Mobiles, DSLR cameras, tabs, webcams etc. consequence, the authentication and validation of a given digital content have become more difficult due to the possible diverse origins and the potential alterations that could have been performed on them. So this will be in great use during the forensics investigations which ask for mainly the evidence to prove the case. There are many methods to identify the camera from the image but they are not effective in every means like they cannot clearly classify the models or the same company camera etc. There have been many methods introduced to identify the camera from the image. The process of generating a photo using an ordinary digital camera is illustrated in Fig. 1.1. The light from the scene is entered through a set of lenses and passes through an anti-aliasing filter. It then reaches a colour filter array (CFA) that is intended to admit one of the red (R), green (G) and blue (B) components of the light per pixel. This is for the semi-conductor sensor which converts signal into electronic form. A de-mosaicing process is also carried out subsequently. This is the process of obtaining the intensities of other two colours, for each pixel. This is obtained by interpolating the colour information within a neighbourhood. A sequence of image processing operations, such as colour correction, white balancing etc is also

done. Before the image is saved it undergoes Gamma correction, enhancing, JPEG compression, etc.

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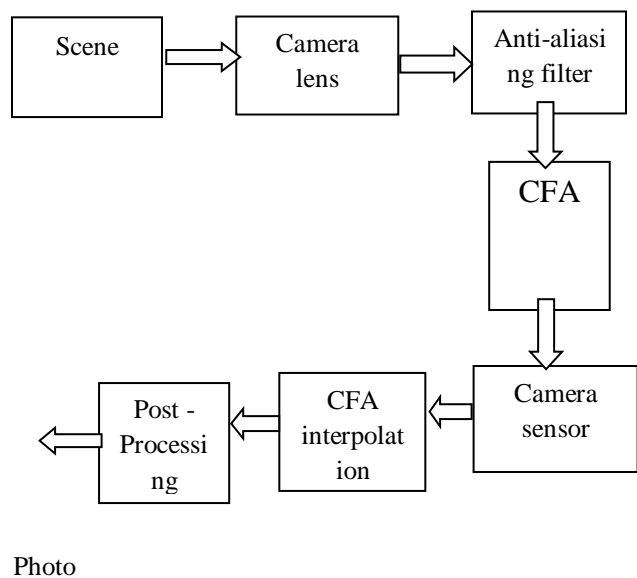


Fig 1:- Image formation in a camera

II. LITERATURE SURVEY

There are different methods in identifying the source camera from an image. One such method is proposed by the method in [3] using an algorithm for identifying and classifying colour interpolation in image. It is proposed based on two methods : first to analyse the correlation of each pixel value with its neighbor values by using an algorithm, and second by an analysing the difference between the pixels independently. Another such method is to identify the source camera from the its image is by analyzing lens aberration noise. During the image generation process the lens system can introduce some aberrations like spherical, coma, field curvature, radial distortion and chromatic aberration. The lens radial distortion is proposed in [4] as the best technique for source camera identification. Straight lines will appears as curves if the lens undergoes radial distortion. The radial distortion degree of each image can be measured by three steps: edge detection, distorted segment extraction, and distortion error measurement. It is necessary to extract statistical features to identify the source camera from its image that can be used to discriminate between cameras. Kharrazi, et al. [20] used image color statistics of images, which is the combination of interpolation and color processing. Image quality metrics are also being used to measure the differences arising from image processing operations. The non-linearities produced from cameras are introducing higher-order correlations in the frequency domain, which can be detected using polyspectral analysis tools [10]. Farid and colleagues [9–11] have used bi-coherence statistics to estimate geometric and luminance non-linearities and to calibrate digital images. We employ polyspectral analysis and higher-order statistics as discriminating features primarily because of their sensitivity to the non-linear distortions produced by digital cameras. The use of wavelet coefficient statistics is motivated by their effectiveness in steganalysis [18] and image origin identification [19].

Methods based on sensor pattern noise [12-15] have drawn much attention due to the relaxation of the similar assumptions. Advantages of using sensor pattern noise is that it can identify not only camera models, but also individual cameras from the same model can be identified [1, 6]. The different sensitivity of pixels to light due to the in homogeneity of silicon wafers [16, 17] is also a reason to cause sensor pattern noise. The SPN is also caused by imperfections during the sensor manufacturing process. This property makes sensor pattern noise a robust fingerprint in identifying and linking source devices and verifying the integrity of images.

The DWT-PCA Based Copy-move Image Forgery Detection, Michael Zimba and Sun Xingming [1] has investigated result on image forgery detection specifically on copy-move using improved algorithm on Discrete wavelet transform and Principal component analysis –Eigen value Decomposition. The proposed method uses the application of Principal Component Analysis and Eigenvalue Decomposition (PCA-EVD). This is used in reducing the dimension of the feature vector. Combination DWT and PCA is used to develop an improved version image forgery detection.

The experimental results indicate that the dimension of the features is reduced compared with the existing related algorithms, at the same time, the accuracy of detection is good.

Locally Adaptive DCT Filtering for Signal-Dependent Noise Removal by Rusen O' ktem, I Karen Egiastian et.al., [22] proposed in their work mentions the problem of signal-dependent noise removal in images. DCT is expected to approximate the Karhunen-Loeve decorrelating transform. It enables effective suppression of noise components since it is being applied locally, that is, within a window of small support. The preservation ability of the filter, allowing not to destroy any valuable content in images is especially advantage and considered. In this work, they aim to develop a class of transform based adaptive filters capable of suppressing signal dependent and multiplicative noise. Preserving *texture, edges, and details*, containing significant information for further processing and interpreting of images.

In Discrete cosine transform–based local adaptive filtering of images corrupted by nonstationary noise by Vladimir V. Lukin, Dmitriy V. Fevralev et.al., [23], observed that the images are contaminated by a nonstationary noise. This will not provide any information on noise dependence on local mean or about local properties of noise statistics that is already available. In order to remove such noise, a locally adaptive filtering has to be applied. Two mechanisms of local adaptation are proposed and are applied. The first one takes into account local estimates of noise standard deviation. The second one exploits discrimination of homogeneous and heterogeneous image regions by adaptive threshold setting

In Digital Camera Identification From Sensor Pattern Noise by Jan Luká's, Jessica Fridrich [24] propose a new method for the problem of source camera identification from its images based on the sensor pattern noise. For each camera under investigation, image's unique identification fingerprint, the sensor pattern noise is determined. This is achieved by using a denoising filter which averages the noise obtained from multiple images.

Determining Image Origin and Integrity Using Sensor Noise by Mo Chen, Jessica Fridrich [25] proposed a unified framework that is used to identify the source of digital camera from its images. Also this method is used for revealing digitally altered images that is for determining forgery using photo-response non-uniformity noise (PRNU), which is also called as digital image forgery detection. The PRNU is estimated from maximum-likelihood estimator. Digital forensics results are then achieved by detecting the presence of sensor PRNU, from specific regions of the image under investigation. The robustness of the proposed forensic methods is tested on common image processing, such as JPEG compression, gamma correction, resizing, and denoising.

In Classification of digital camera-models based on demosaicing artifacts by Sevinc Bayram, Husrev T. Sencar, Nasir

Memon[26] used traces of demosaicing operation in digital cameras. They formulated two methods which also defined a set of image characteristics. Different methods were tried in which one method tries to estimate demosaicing parameters. Assuming to be a linear model. Another method is done by extracting periodicity features to detect simple forms of demosaicing. They considered both images taken under similar settings at fixed sceneries and images taken under independent conditions, to determine the reliability of the designated image features in differentiating the source camera-model.

III. PROPOSED SYSTEM

A. Methodology

Here we are using mainly two methods to detect our source camera. One is the DCT method and other is DWT method. Both these methods yields the same result but the difference in the methods depends on the accuracy of the result and also the time taken to achieve our aim.

First we are going to explain in detail about the steps used in DCT method. The steps in both DCT and DWT are same that is extracting the image noise and from the noise we are finding a way to differentiate the images from different camera. In DCT we cannot find the exact features of the image or noise. DCT is mainly used for compression technique rather than to get the image details.

B. Source camera identification using DCT

In our proposed system DCT method follows different steps to extract the noise and also some normalization to do the same. First step of source camera identification is to extract the noise from the image. We are extracting PRNU noise from the image using LADCT method. Simple DCT method is not efficient as we have seen from the previous chapters. LADCT is Locally Adaptive Discrete Cosine Transform which is applied block wise. So the image is first divided to its red, blue and green blocks and then it is divided to blocks. Each red, green, blue is divided into blocks of images. Then LADCT is applied to each block of the image and noise extracted from each block. Now the result we obtained will not be an accurate result since each block has different intensity and also the characteristics of each block vary so we apply an averaging of the noise as the next step. The problem here is we cannot apply the same averaging value or the threshold value to each and every block so here we are applying an weighted averaging method which can be applied to each block irrespective of their characteristics.

C. Locally Adaptive DCT filter

In this paper we are mainly focusing on Locally Adaptive DCT filter rather than normal DCT filter. For feature extraction, quality assessment, filtering, and compression pixel. [5] of images Discrete Cosine Transform is mainly adopted widely nowadays. Locally adaptive filters are here applied due to its exceeding advantages of the same in full images and especially in wavelets determination and PRNU extraction that is the multiplicative

noise. Since we need to extract PRNU from these images we are mainly focusing on LADCT rather than the simple DCT method.

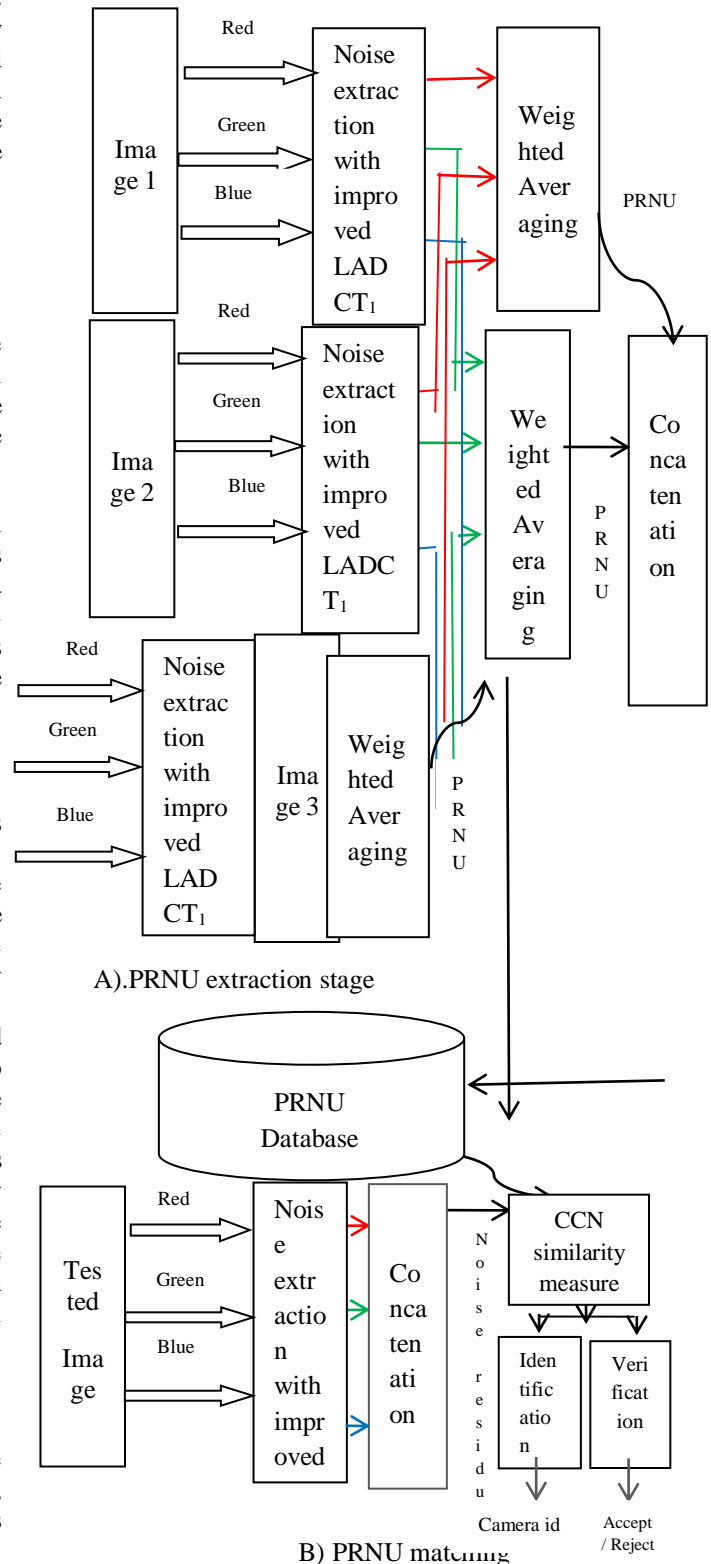


Fig 2:- Proposed system

D. Prnu Extraction

The above fig 2. shows the working of our proposed system. ‘n’ images are selected from a camera which is used for training purpose, then each image is converted to its red, green and blue channels separately. Then the steps below are executed one by one to achieve our aim:

- 1.Images are divided into blocks of $u \times u$ pixels.Let S be a horizontal or vertical shift ($S =$ between two consecutive blocks. According to [37], $u = 8$ and $S = 1$ is chosen for best performance.
2. For each block b whose upper left corner is at (m, l) , DCT coefficients are computed as:

$$B(p,q) = c(p).c(q)x \sum_{m=0}^{u-1} \sum_{l=0}^{u-1} b(m,l) \cos\left(\frac{(2m+1)p\pi}{2u}\right) \cos\left(\frac{(2l+1)q\pi}{2u}\right)$$

Where

$$c(i) = \begin{cases} \sqrt{\frac{2}{u}}, & \text{if } 1 \leq i \leq u - 1 \\ \frac{1}{\sqrt{u}}, & i = 0 \end{cases}$$

3. A threshold is computed for each block as

$$T = k\sigma_b$$

Where k is a constant which takes the value of 2.6 that controls the value of threshold.

- 4.Further hard thresholding is applied on each block as follows :

$$B'(p,q) = \begin{cases} B(p,q), & \text{if } |B(p,q)| > T \\ 0, & \text{Otherwise} \end{cases}$$

5. The following equation is used for getting the inverse DCT, for reconstructing the processed blocks :

$$b'(m,l) = c(p)c(q)x \sum_{p=0}^{u-1} \sum_{q=0}^{u-1} B'(p,q) \cos\left(\frac{(2m+1)p\pi}{2u}\right) * \cos\left(\frac{(2l+1)q\pi}{2u}\right)$$

6. The final estimate is computed by taking the average of the result obtained from combining each blocks.

We have said in the beginning of this chapter about taking the threshold value for each blocks that there can be issue in regarding the variation in image characteristics at each block. So here we are using a threshold value depending on the characteristics of each block. It consists of two phases mainly. One step is taking the estimate of the sensor pattern noise extracted which is calculated as :

$$\hat{K} = \frac{\sum_{i=1}^N (I_i - f(I_i))}{\sum_{i=1}^N f(I_i)}$$

Where I_i is the observed image and $f(I_i)$ is it's filtered version with LADCT $\sigma^2 = 0.002.n_K$ the estimation noise for K can be written as:

$$\hat{K} = K + \eta_K$$

For a block b , we can calculate its noise as follows :

$$I_b \approx I_b^0 + I_b^0 K_b$$

Then the block dependent threshold can written as[28]:

$$T_b = k\sigma_b$$

where k is constant and can be calculated empirically. Also additive noise can be calculated as[28]

$$\sigma_b^2 \approx E[b^2] \sigma_{K_b}^2$$

E. Weighted Averaging

As discussed earlier we are determining the sensor pattern noise from n images, denoted by L be the number of samples of images placed in the direction of vertical of horizontal. The corresponding noise residue[27] can be expressed as follows:

$$r_i(j) \approx I_i^0(j)K(j) + \Phi_i(j) \text{ where } j=1,2,..L$$

Where Φ_i is an independent noise. We are taking into an assumption here that the images are all having smooth regions and same color content.Here we are mainly focusing on the sensor pattern noise K . An unknown signal $s(j)$ with $j=1,2,..,L$ is the PRNU from a set on N images. In a noisy environment with N

noisy observations. Estimation of $s(j)$ can be determined from the following formula

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

Where $r(i)$ is the sum of a signal and a noisy factor Ψ_i . This method is known as constant averaging. But the problem here with constant averaging is that the noise variance will differ in different observations so we tend to give another way to calculate the same. So here we apply weighted average technique, which is described as follows [27]

$$w_i = \frac{1}{\sigma_i^2} \left(\frac{1}{\sum_{k=1}^N \frac{1}{\sigma_k^2}} \right)$$

Where w_i is the weight corresponding to i th noise residue r_i . The optimal weight for the i th observation is given by[27-28]

$$\sigma_i^2 = \frac{\sum_{j=1}^L (\hat{n}_i(j) - \bar{n}_i)^2}{L}$$

The weight also depends on undesirable noise Ψ_i in each observation. The estimated noise variance can be computed as[27-28]

$$\hat{n}_i(j) = r_i(j) - \bar{r}(j)$$

with

$$PRNU(j) = \sum_{i=1}^N w_i r_i(j)$$

Where n_i denotes the mean of the estimated noise n_i and

$$\bar{r}(j) = \frac{1}{N} \sum_{i=1}^N r_i(j)$$

Represents the average signal. The final PRNU estimated with WA technique is given by

$$PRNU(j) = \sum_{i=1}^N w_i r_i(j)$$

F. Color PRNU Concatenation

PRNU consists of color channel to take into consideration at each pixel location which is a challenging task. There have been a lot PRNU estimation techniques today. The one which is mainly used is the Luminance component, this is rule for estimating the PRNU. This is described as Y [27]

$$Y = 0.30I_R + 0.59I_G + 0.11I_B$$

Where I_R, I_G, I_B represents red, green blue color respectively. In this work, the PRNU is estimated from each channel the Red, Blue and Green separately and then the resulting PRNUs are concatenated to form a color PRNU. Similarly, a color noise residue can be obtained from the test image by concatenating the noise residues of the red, green, blue channels.

1. Source camera Identification Using DWT

DWT is used in lossless image compression of gray level image. L represent the low-pass filtered signal L (low frequency) allows the perfect reconstruction of original Image. H represents the high-pass filtered signal. The DWT represents the two images representing the technique to transform the DWT process. Then the DWT image will move on to the quantization process. That the process is doing again and again to get the best result. Thus the output of the DWT image compression is good. The quality of the DWT image is also good. The method Discrete Wavelet Transform is mainly used in the images for determining its very minute features like extracting the noise and further performing processing in the signal to attain certain criteria and feature extraction from signals.

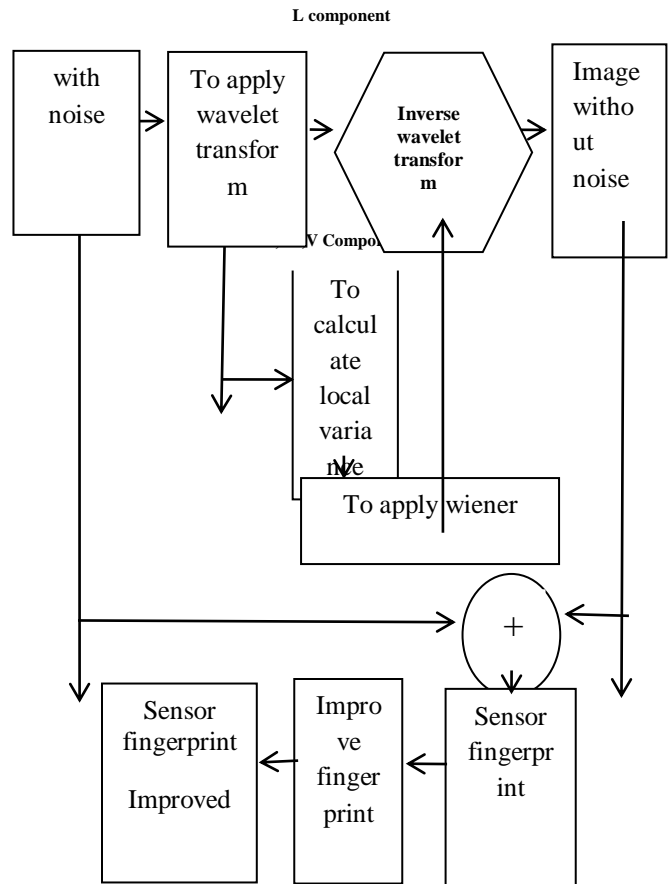


Fig 3:- DWT method

The above fig 3. shows the steps and the flow chart of the DWT method in identifying the source of an image. Here we use two algorithms mainly to extract PRNU and the second one to extract the features from the PRNU. To extract the noise pattern first the image is divided into red, green, blue channels respectively. Then, a four-level wavelet decomposition of each colour channel is calculated using the Daubechies, 8-tap, separable quadrate mirror filters. The number of decomposition levels can be increased to improve accuracy or to reduce processing time.

For each level of decomposition (H,V,D) Horizontal, vertical and diagonal high-frequency images are obtained. For each detail image, the local scene variance is estimated. Four estimates are obtained with window sizes corresponding to {3, 5, 7, 9}. Finally, we choose the estimate which maximises the a posteriori probability[27].

$$\sigma^2(i,j) = \max \left(0, \frac{1}{W^2} \sum_{(i,j) \in N} c^2(i,j) - \sigma_0^2 \right), (i,j) \in J$$

The algorithm for the calculation of PRNU extraction is as below:

Algorithm 1:

Input: Image I

Variance estimation adaptive or non-adaptive.

Result: Sensor Fingerprint Noise

1.Procedure: Extract PRNU

2.A 4-level wavelet decomposition is applied to image I

3.Foreach wavelet decomposition do

4.Foreach component c belongs to{H,V,D} do,

5.Compute local variance

6.If adaptive variance then

7. Compute 4 variances with window sizes 3,5,7,9

Minimum variance is selected

8. Else ,variance is computed with window size 3

9.Apply Wiener Filter and compute the noiseless wavelet components

Obtain I_{clean} by applying Inverse Wavelet Transform

10.Obtain sensor noise with

$I_{\text{noise}} = I - I_{\text{clean}}$

11.Zero-meaning is applied to I_{noise}

12.The green channel weight is increased with

$I_{\text{noise}} = 0.3 \cdot I_{\text{noiseR}} + 0.6 \cdot I_{\text{noiseG}} + 0.1 \cdot I_{\text{noiseB}}$

Once the PRNU is extracted it is subjected to feature extraction using the Daubechies 8 wavelet feature extraction technique. Best estimate is chosen from a set of minimum four variances.[27].

$$\hat{\sigma}^2(i,j) = \min \left(\sigma_3^2(i,j), \sigma_5^2(i,j), \sigma_7^2(i,j), \sigma_9^2(i,j) \right), (i,j) \in J$$

By calculating the inverse transform and also by subtracting the denoised image from the original image we get the noise

residual. JPEG and demosaicing artefacts, presented in the noise image are subtracted by the mean column and row values [7]. Since the configuration of the colour matrix green channel contains more information about the image green channel is given more weight.[8-9]. For the purpose of classification we need to get the features from the sensor fingerprint which is the next step.81 features (3 channels \times 3 wavelet components \times 9 central moments) is extracted totally. Classification was performed using a SVM. We used the LibSVM package in which the SVM is extended to multiple classes yielding class probability estimates

IV. RESULT AND ANALYSIS

We have discussed about the steps we used identify the source of the image using two methods respectively the DCT and the DWT.This chapter will show us the result in we obtain in the DCT and DWT process.

The algorithm for feature extraction and PRNU extraction are implemented in Matlab 2016. In a Intel Core i7 3.5 GHz and 8GB of RAM it takes approximately 30s to extract the PRNU and compute the features for a 1024×1024 crop of an image. Also it takes 5 s for a 512×512 crop of an image using adaptative variance estimation and zero meaning.

The result shows that the DWT method is more accurate compared to that of LADCT method. We can always rely upon DWT based noise extraction and also feature extraction from the noise which is not available in LADCT method.

A. Data set

In this work, we took a set of sample images randomly, for training and testing the purposes. A random of 100 samples were used for training the image set. Also in DCT we used the Dresden image dataset is used to compare the noise features and noise elements to finally get the result. Dresden image dataset consists of pre-stored image noise and features from a set of different cameras which can be used to compare our noise results with.

B. Experimental Results

The proposed method is successfully implemented on the image data sets. The following results have been generated.The following result is for the source camera identification using the DWT method.

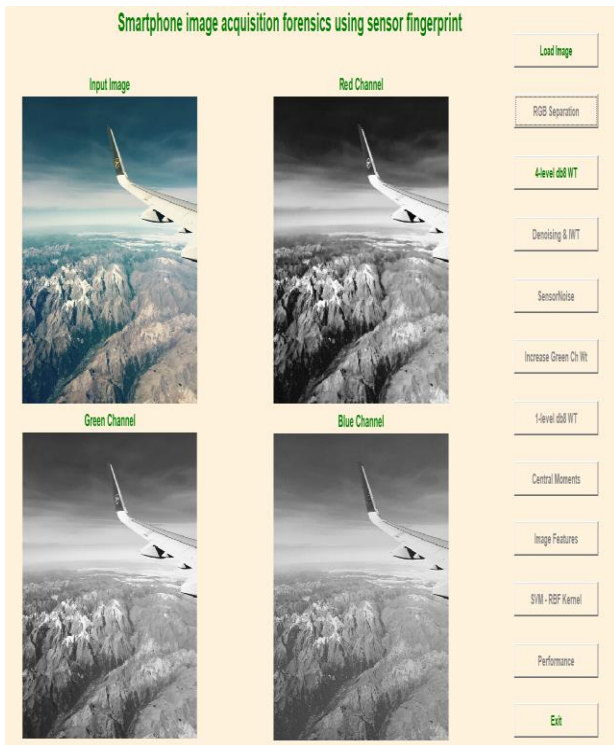


Fig 4:- RGB Separation of the Input Image

Fig 4. shows the RGB separation of the input image. Fig 5. (a) shows the results of 4-level DWT done in the input image. The below figure is only for the blue channel the same is happening for the red and green channel respectively

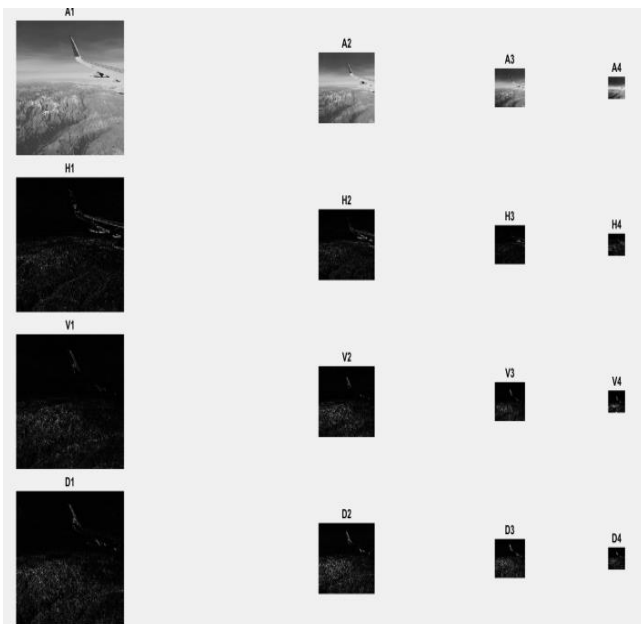


Fig 5:- Application of 4-level DWT

Fig 6. shows the image after filtering the unwanted noise.

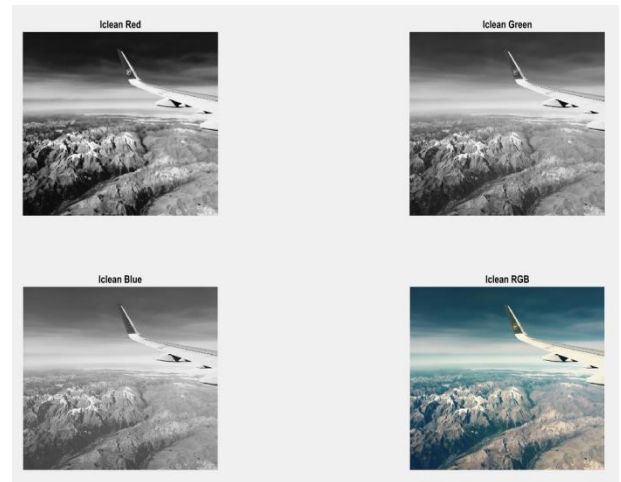


Fig 6:- Denoised input image

Fig 7. shows the result of sensor noise. The extracted noise from the image is shown in this figure or step.

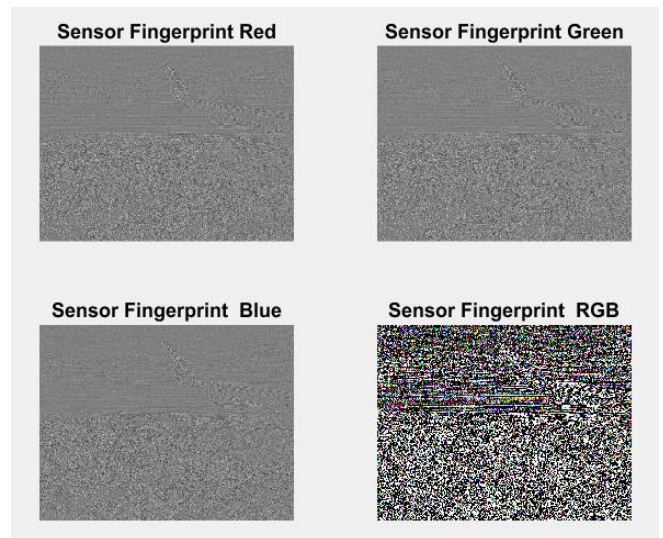


Fig 7:- Sensor Noise

Fig 8. shows the improved sensor fingerprint which is done for green channel only which is effected on all R,G and B

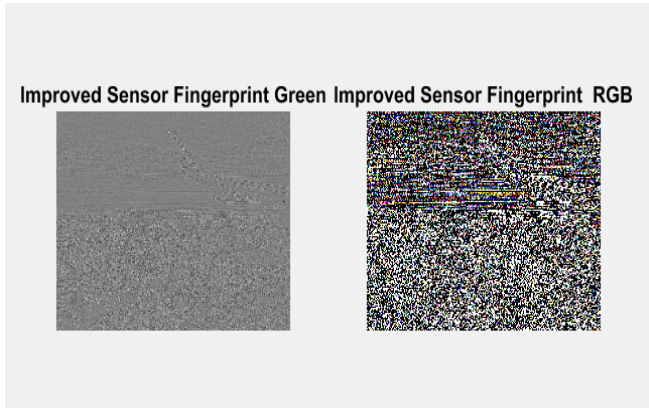


Fig 8:- Improved Sensor Pattern Noise

Fig 9. shows the Horizontal , Vertical and Diagonal extraction of the image features from the noise. 1 level DWT.

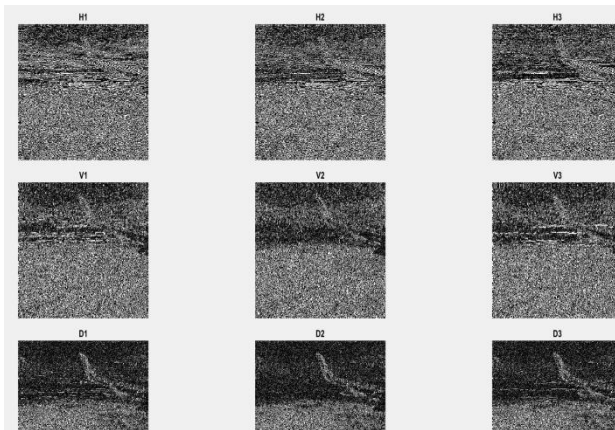


Fig 9:- Image feature extraction

Fig 10. The next step is to calculate the central moment from the image. Total of 81 features are being extracted from the horizontal , vertical and diagonal images.

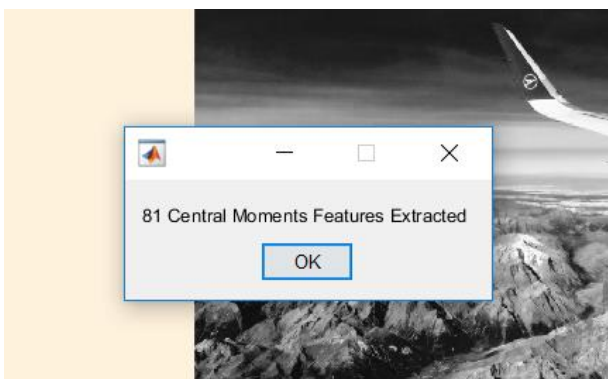


Fig 10:- Central Moment Calculation

The Fig 11. shows the final result of our DWT method. The image is being identified from which source it has been taken. The input image we given was the iphone 6plus and result shows correct.

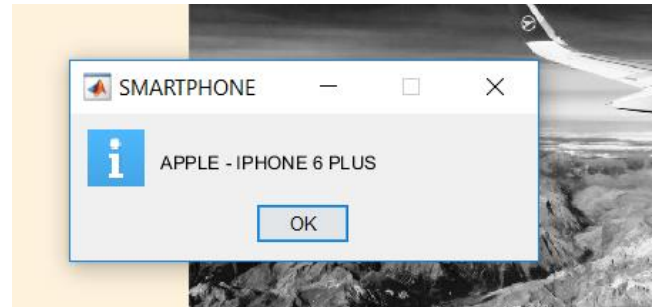


Fig 11:- Source camera identification of the image

The following experiment results are for the source camera identification using the LADCT method. Here we use the image data set with a set of images from canon and Nikon. Then its PRNU are extracted using the method of LADCT and then by the weighted average method a average PRNU has been finally obtained and stored in the PRNU test document which is then trained with test images to show whether the images match. The output of the image yields the exact result that of the input image or the source is correctly identified.

Following figures shows the process flow :

canon	05-02-2018 20:43	File folder
nikon	05-02-2018 20:43	File folder
test images	05-02-2018 20:43	File folder

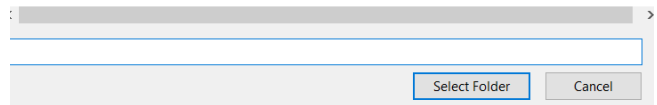


Fig 12:- Choose the folder to extract the PRNU

Similarly the next folder is also selected. We can train the images similarly for any type of camera in the real world. Such PRNU from the images are stored and can be kept to further used to test the images prove the cases and can be taken for investigations.

The code is made to run again to train the test image folder. The test image folder consists of images from both canon folder and Nikon folder and they are differentiated effectively.


```

Command Window
nikon
canon
canon
canon
canon
canon
fx >>

```

Fig 13:- Source camera identified

The above figure shows the exact image that has been checked to identify the source. The images in the test folder is of the form as shown in the fig 13.

In this work we have implemented two different methods to identify the source of the camera in which DWT is a better method compared to DCT in case of accuracy. All the methods can be treated as best methods but here we could consider DWT as a better option since only one image is trained in such a way to get the result. DCT can be also used but to get a set of images from a particular camera and training those images to find the PRNU is a tiresome and time consuming process. Also DWT can be treated as a much better option in the sense that DWT used feature extraction from within the noise itself where in DCT only the noise as itself is used and it's average is used for the identifying purpose.

V. CONCLUSION

In this work we have implemented two different methods to identify the source of the camera in which DWT is a better method compared to DCT in case of accuracy. All the methods can be treated as best methods but here we could consider DWT as a better option since only one image is trained in such a way to get the result. DCT can be also used but to get a set of images from a particular camera and training those images to find the PRNU is a tiresome and time consuming process. Also DWT can be treated as a much better option in the sense that DWT used feature extraction from within the noise itself where in DCT only the noise as itself is used and it's average is used for the identifying purpose. This can also be improved to be used in future work. The method can be used in such a way that lens dust identification these are the minute dust particles within the lens which are been there from the manufacturing defect. They are negligible in the sense while taking an image but they are very grateful while forensic investigation. These methods can also be used to embed the camera specific features within the camera in such a way that as soon as the image is taken and is stored the camera specific

features are also being embedded within the image in an encrypted form so that they can be used during forensic investigations.

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