An Efficient Camera Identification Technique using Krawtchouk Moment Invariants

1Megha Borole, 2Prof. S. R. Kolhe

1Research Scholar, School of Computer Science, North Maharashtra University, Jalgaon, India
2Professor, School of Computer Science, North Maharashtra University, Jalgaon, India

Email: 1megha.borole@gmail.com, 2srkolhe2000@gmail.com

https://doi.org/10.26782/jmcms.2019.02.00004

Abstract

In late years, camera identification methods have drawn attention in the area of digital forensics. To detect the source camera through which the picture is caught, Photo-Response Non uniformity (PRNU) noise is utilized as a camera, impression, as it is a particular component that recognizes pictures taken from the comparable cameras. This paper introduces a camera identification technique which is based on Krawtchouk Moment invariant features. The Photo Response Non-Uniformity (PRNU) noise is a type of sensor finger impression, which permits to extraordinarily distinguish the camera that took an image. It is estimated from the denoised images using a denoised filter. Then estimate the Krawtchouk Moment invariants from the PRNU noise pattern. The Krawtchouk Moments are invariant to scaling, translation, rotation, and shear. These invariants are fed to Fuzzy Min-Max Neural Network with Compensatory Neuron (FMCN) and by performing ten-fold cross-validation technique, verification is made out. The experimental results show that the proposed technique achieves an average accuracy of 93.3% for first experiment and 98.3% for the second experiment.

Keywords: Camera identification; photo response non-uniformity (PRNU); Krawtchouk moments; fuzzy min-max neural network with compensatory neuron (FMCN)

I. Introduction

These days as the digital camera is winding up increasingly advantageous for photograph capturing, digital images can be discovered wherever in the present everyday life. Nowadays everybody has a capacity of recording, saving and sharing a large number of digital images with the use of actively growing inexpensive and user-friendly devices that enables the use of visual data, also easy availability of image
processing tools makes the editing job easy [I][XXI]. In many situations, computerized data starts from an obscure or untrusted source. At the point when this happens, a falsifier or attacker can effortlessly operate digital content, for example, pictures or video to make perceptually reasonable frauds [XI]. The steps of image acquisition process inside of the camera that add the artifacts to the contents of the image which will give distinctive features for the process of identification [II].

In this paper, an efficient camera identification technique is proposed. In section 2, we discuss the related work. In Section 3, we discuss our proposed approach. Experimental results and discussion are given in section 4.

II. Related Work

In relation to the previous work, use of the artifacts is to collect features, proposed by researchers. Kharrazi et al. [XII], proposed a system, which is utilized to recognize the source camera. In this method, they utilize three feature sets to perform identification of camera model. An Image Quality Metrics (IQM), color features, wavelet domain statistics are the three feature sets and they are used for classification. S. Bayram et al. [XVII], used the color filter array (CFA) interpolation process. For image classification, correlation structure present in each color band is used, which is determined by CFA interpolation process.

Based on sensor’s pattern noise of image, Lukas et al. [IX], identify the camera. For each analysis, they first find its reference pattern noise. They take reference of pattern noise as a spread-spectrum watermark, whose occurrence in the image is made by using a correlation detector, to distinguish the camera for a given picture. Based on sensor’s pattern noise Y. Sutcu et al. [XXII], suggests an enhancement over identification of source camera. To advance the applicability of the method, they propose a development over it by additionally checking that class properties of the image being referred to are as per those of the camera.

To identify the source cell-phone camera, O. Celiktutan et al. [XIV] uses a subset of Kharrazi’s feature sets. After that features of binary similarity measures to earlier feature sets to get 592 features added. F. Meng et al. [V], presents a new feature-based technique. The technique utilizes bi-coherence and wavelet coefficient as a feature, which is extracted from digital images. The method relies upon an imaging pipeline analysis and processing operations of the digital camera. To choose the features, this strategy utilizes the sequential forward feature selection algorithm and for classification, a support vector machine.

T.Filler et al. [XIX], presented a technique that utilizes 28 features identified with statistical moments and correlations of the linear pattern. G. Xu et al. [VII], utilizes a statistical feature (59-dimensional Local Binary Patterns (LBP) set) from each color channel by considering 8-neighbor binary co-occurrence for camera model identification. Yoichi Tomioka et al. [XXIII], proposed a method to distinguish the camera, which depends on clusters of pixels pairwise associations. To decrease the impacts of noise contamination, grouping the pixels according to the PRNU noise estimation of the tested camera. In [VI], based on the local binary pattern of extracted edges from the input image, a new single image feature is proposed.
I. Amerini et al. [VIII], proposed a procedure that depends upon Normalized Cuts rule and it doesn’t from the prior require the data of the measure of classes in which the dataset must be secluded yet it needs simply stop limit. Amel Tuama et al. [II], developed a technique which extracts the three sets of features (co-occurrences matrix, characteristics associated to CFA interpolation arrangement and conditional probability statistics) in a machine learning structure for identification of digital camera. They enhance the identification rate by adding the bigger set of features.

III. Proposed Camera Identification Approach

III.i System Framework

The proposed camera identification framework as shown in figure 1, uses the PRNU as a characteristic to identify the camera. An image denoising, PRNU noise extraction and Krawtchouk moment feature extraction and FMCN training and classification are the key processing points. The camera identification technique using proposed feature-based approach is summarized in the algorithm.

![Figure 1: Proposed Camera Identification Framework](image)

Algorithm: Camera Identification

**Input:**
- **img**: The original image (JPEG format).
- **Feat Extracted**: Matrix of moment invariants extracted from the image database.
- **T Data**: trained dataset

**Output:**
- **c**: Camera Model.

**Procedure**
1. Read the input original image **img**.
2. Denoise the input image using denoising filter (Gaussian-based / Wavelet-based filter).
Evaluate the PRNU pattern $f_{ij}$, for Img using:

$$f_{ij} = \frac{1}{m \times n} \sum_{k} f_{ij}^{(k)}$$

4. Estimate the Krawtchouk moment invariants,

$$[Q_{20}, Q_{02}, Q_{12}, Q_{21}, Q_{30}, Q_{03}]$$

for each PRNU pattern $f_{ij}$ and store in feat Extracted.

5. Load the train Data and categorize the input image with trained dataset using FMCN classifier and get the camera model $c$ of the image.

**End**

### III.ii Image Denoising and PRNU Noise Extraction

The small deficiencies of sensors produce deviations in their response to a digital camera, which is generally demonstrated as a multiplicative noise $K$. This multiplicative noise is called Photo Response Non-Uniformity (PRNU) Noise. PRNU is a type of sensor finger impression, which permits to extraordinarily distinguish the camera that took an image. PRNU noise shows an alternate noise pattern for each picture sensor and if the various pictures are taken of a similar scene it remains around same. The sensor output of the camera is as follows [IX]:

$$y_{ij} = f_{ij} (x_{ij} + \eta_{ij}) + c_{ij} + \varepsilon_{ij}$$

where, $f_{ij}$ represents the PRNU noise component, $x_{ij}$ specifies the photon count, $\eta_{ij}$ represents the shot noise, $\varepsilon_{ij}$ represents the additive random noise, $c_{ij}$ is the dark current, $i=1,..,m$ and $j=1,..,n$, where $m \times n$ represents sensor resolution. In an image file, before keeping the signal $y$, it goes through a multifaceted processing. The $p_{ij}$, pixel values are as [IX]:

$$p_{ij} = P\left(y_{ij}, N\left(y_{ij}\right), i, j\right)$$

where, $(i, j)$ indicates pixel location, a nonlinear function of $y_{ij}$ represented by $P$, $N(y_{ij})$ represents local neighborhood of value of $y$.

$$\hat{x}_{ij} = \frac{y_{ij} - \varepsilon_{ij}}{f_{ij}}$$

In equation (3), pixels values are corrected [IX], an approximation to $f_{ij}$ is represented by $\hat{f}_{ij}$ and is acquired by taking the average of scenes $f_{ij}^{(k)}$, $k=1,\ldots,K$.

$$\hat{f}_{ij} = \frac{1}{m \times n} \sum_{k} f_{ij}^{(k)}$$
In a practical environment, wavelet-based denoising filter (WF) [XIII] utilize for denoising the image. To suppress the components having low frequency, noise residual $N_I$ is acquired by subtracting the denoised image from the input image I. Here, $F$ indicates the denoising filter [X][XVIII].

$$N_I = I - F(I) \quad (5)$$

### III.iii Features Extraction

Krawtchouk moments [XV] [III] [XVI] are used for the feature extraction technique. By utilizing Krawtchouk polynomials as the basis function set, Krawtchouk moments are framed, which are invariant to scaling, translation, rotation, and shear. The Krawtchouk moments are orthogonally stable.

#### III.iii.a Krawtchouk polynomials

The standard $n$th order Krawtchouk polynomial is well-defined as:

$$k_n(x; p, N) = \sum_{k=0}^{N} a_{k,n,p} x^k = 2F_1 \left( -n, -x, -N; \frac{1}{p} \right) \quad (6)$$

Where $x, n = 0, 1, 2, ..., N, N > 0$, $p \in (0,1)$. The hyper geometric function is denoted as $2F_1$, and defined as

$$2F_1(a, b, c; z) = \sum_{k=0}^{\infty} \frac{(a)_k (b)_k z^k}{(c)_k k!} \quad (7)$$

and the pochhammer symbol $(a)_{k}$ is given by

$$(a)_{k} = a(a + 1) \ldots (a + k - 1) = \frac{\Gamma(a+k)}{\Gamma(a)} \quad (8)$$

The $\{ k_n(x; p, N) \}$ forms a complete set of discrete basis functions, which is a set of $(N+1)$ krawtchouk polynomials with weight function

$$w(x; p, N) = \binom{N}{x} p^x (1-p)^{N-x} \quad (9)$$

And fulfills the orthogonality condition

$$\sum_{x=0}^{N} w(x; p, N) k_n(x; p, N) k_m(x; p, N) = \rho(n; p, N) \delta_{nm} \quad (10)$$

Where $n, m = 1, 2, ..., N$ and

$$\rho(n; p, N) = (-1)^n \left( \frac{1-p}{p} \right)^n \frac{n!}{(-N)_n} \quad (11)$$

Following are the Krawtchouk polynomials examples up to the second order:

$$k_0(x; p, N) = 1 \quad (12)$$

$$k_1(x; p, N) = 1 - \left[ \frac{1}{N_p} \right] x \quad (13)$$

$$k_2(x; p, N) = 1 - \left[ \frac{2}{N_p} + \frac{1}{N(N-1)p^2} \right] x + \left[ \frac{1}{N(N-1)p^2} \right] x^2 \quad (14)$$
III.iii.b Weighted Krawtchouk Polynomials

The regular strategy for keeping away from numerical changes for moment calculations is by methods for normalization by the norm. With respect to the norm $\tilde{K}_n(x; p, N)$, the normalized Krawtchouk polynomials is defined as:

$$k_n(x; p, N) = \frac{\bar{K}_n(x; p, N)}{\rho(n; p, N)}$$

Following is the definition of $\tilde{K}_n(x; p, N)$, which is a set of weighted Krawtchouk polynomials:

$$\tilde{K}_n(x; p, N) = K_n(x; p, N) \frac{\rho(n; p, N)}{\rho(x; p, N)}$$

The orthogonality condition turns out to be

$$\sum_{x=0}^{N-1} \tilde{K}_n(x; p, N) \bar{K}_m(x; p, N) = \delta_m$$

III.iii.c Krawtchouk Moments

The local features of an image are able to extract by Krawtchouk moments. For an image with intensity function $f(x, y)$, (n+m) order Krawtchouk moments with regard to weighted Krawtchouk polynomials are defined as,

$$Q_{nm} = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \tilde{K}_n(x; p1, N - 1) \bar{K}_m(y; p2, M - 1) f(x, y)$$

To match the $N \times M$ pixel points of an image, parameters N and M are interchanged with N-1 and M-1 respectively. The Krawtchouk moment equivalent to $n = m = 0$ is the weighted mass of the image, i.e.,

$$Q_{00} = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \sqrt{w(x; p1, N - 1)w(y; p2, M - 1)} f(x, y)$$

By solving (17) and (18) for $f(x, y)$, the image intensity function can be written with regard to Krawtchouk moments, i.e.,

$$f(x, y) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} Q_{nm} \tilde{K}_n(x; p1, N - 1) \bar{K}_m(y; p2, M - 1)$$

A series of weighted Krawtchouk polynomials weighted by the Krawtchouk moments is another approach for representation of image intensity function. If the moments are limited to order $0 \leq p < 2N-2$, the series is reduced to

$$f(x, y) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \phi(n - m, m, x, y)$$

$$\phi(k, l, x, y) = \begin{cases} Q_{nm} \tilde{K}_n(x; p1, N - 1) \bar{K}_m(y; p2, M - 1) k \in S_N, l \in S_M \\ 0 & \text{others} \end{cases}$$
where $S_N = \{0, 1, 2, \ldots, N - 1\}$ and $S_M = \{0, 1, 2, \ldots, M - 1\}$. The product of $f(x, y)$ and $k_n(x; p1, N - 1)k_m(y; p2, N - 1)$ are the Krawtchouk moments observe from (18).

Therefore, extraction of the local features at different positions of an image by the lower order Krawtchouk Moments, empower by the proper selection of $p1$ and $p2$. It can be appeared by using Parseval’s theorem.

$$\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} |f(x, y)|^2 = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} [Q_{nm}]^2$$

(23)

An information of an image for a specific region of interest store in the low order Krawtchouk Moments, rest of the image information stored in higher order moments.

### III.iii.d. Krawtchouk Moment Invariant

Using discrete sum approximation, geometric moments of an image is defined as

$$M_{nm} = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} x^n y^m f(x, y)$$

(24)

Following equation represents the standard set of geometric moment invariants, which are independent to the rotation, scaling and translation.

$$V_{nm} = M_{00}^{N-1} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} [(x - \bar{x})\cos\theta + (y - \bar{y})\sin\theta]^n \times [(y - \bar{y})\cos\theta + (x - \bar{x})\sin\theta]^m f(x, y)$$

(25)

Where

$$\gamma = \frac{n + m}{2} + 1$$

(26)

$$\bar{x} = \frac{M_{10}}{M_{00}}$$

(27)

$$\bar{y} = \frac{M_{01}}{M_{00}}$$

(28)

$$\theta = \frac{1}{2} \tan^{-1} \frac{2\mu_{11}}{\mu_{20} - \mu_{02}}$$

(29)

The interval of angle $\theta$ is $-45^0 \leq \theta \leq 45^0$. The central moments ($\mu_{nm}$) is defined as

$$\mu_{nm} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^n (y - \bar{y})^m f(x, y) dx dy$$

(30)

The Krawtchouk moments of

$$\tilde{f}(x, y) = [w(x)w(y)]^{-\frac{1}{2}} f(x, y)$$

(31)
can be written in terms of the geometric moment as
\[
Q_{nm} = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} k_n(x) k_m(y) f(x, y)
\]
\[
= [\rho(n)\rho(m)]^{-\frac{1}{2}} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} a_{i,n,p_1} a_{j,m,p_2} M_{ij}
\] (32)

where, \( M_{ij} \), up to order \( i = n \) and \( j = m \), weighted by coefficients \( \{a_{k,n,p}\} \). \( Q_{nm} \) is a linear combination of geometric moments. In (32), non-orthogonal geometric moments transform to form the orthogonal Krawtchouk moments. According to (25), as required by Krawtchouk moments, the normalized image does not fall inside the domain of \([0, N-1] \times [0, N-1]\); therefore, it is written as
\[
\tilde{V}_{nm} = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} M_{00}^2 f(x, y)
\]
\[
\times \left\{ (x - \bar{x}) \cos \theta + (y - \bar{y}) \sin \theta \sqrt{\frac{N^2/2}{M_{00}} + \frac{N}{2}} \right\}^m
\]
\[
\times \left\{ (y - \bar{y}) \cos \theta + (x - \bar{x}) \sin \theta \sqrt{\frac{N^2/2}{M_{00}} + \frac{N}{2}} \right\}^n
\] (33)

The above equation can be transcribed in terms of \( \{\tilde{V}_{nm}\} \) as
\[
\tilde{V}_{nm} = \sum_{p=0}^{n} \sum_{q=0}^{m} \binom{n}{p} \binom{m}{q} \frac{N^2/2}{M_{00}}^{p+q+1} \times \left( \frac{N}{2} \right)^{n+m-p-q}
\] (34)

An image is a scale normalized such that \( \tilde{V}_{00} = (N^2/2) \) and the centroid of an image is shifted to \((N/2), (N/2)\). In (34), \( \tilde{V}_{nm} \) is a linear combination of \( \tilde{V}_{pq} \), \( \tilde{V}_{nm} \) for odd \( n \) and/or \( m \) does not vanish for identical images. By replacing the regular geometric moments by their invariant counterparts, a new set of moments can be formed.

From (32),
\[
\tilde{Q}_{nm} = [\rho(n)\rho(m)]^{-\frac{1}{2}} \sum_{i=0}^{n} \sum_{j=0}^{m} a_{i,n,p_1} a_{j,m,p_1} \tilde{V}_{ij}
\] (35)

Preferred these set of moments as Krawtchouk moment invariants, some examples of them are,
\[
\tilde{Q}_{00} = \Omega_{00} \tilde{V}_{00}
\] (36)
\[ Q_{10} = \Omega_{10} \left[ \bar{V}_{00} - \frac{1}{(N-1)P_1} \bar{V}_{10} \right] \]

\[ Q_{01} = \Omega_{01} \left[ \bar{V}_{00} - \frac{1}{(N-1)P_2} \bar{V}_{01} \right] \]

\[ Q_{11} = \Omega_{11} \left[ \bar{V}_{00} - \frac{1}{(N-1)P_1} \bar{V}_{10} \right] \\
- \Omega_{11} \left[ \frac{1}{(N-1)P_2} \bar{V}_{01} + \frac{1}{(N-1)^2P_1P_2} \bar{V}_{11} \right] \]

where

\[ \Omega_{nm} = \left[ \rho(n; P_1, N - 1) \rho(n; P_2, N - 1) \right]^{-\frac{1}{2}} \]

In this case, set the constraints to \( p_1 = p_2 = 0.5 \), so that the position of the moments is at the center of the image. The feature vector is

\[ V = [\tilde{Q}_{20}, \tilde{Q}_{02}, \tilde{Q}_{12}, \tilde{Q}_{21}, \tilde{Q}_{30}, \tilde{Q}_{03}] \]

where \( \tilde{Q}_{nm} \) are the Krawtchouk moment in variants.

III.iv. Classification

To represent the pattern classes hyperbox fuzzy sets used by the Fuzzy Min-Max Neural Network with Compensatory Neuron (FMCN) [IV]. The mentioned method is supervised classification technique. FMCN has reduced classification and gradation errors which enables it to learn data in a single pass and its exciting feature is its performance not related to initialization of expansion coefficient, i.e., maximum hyperbox size estimate. So, in training and testing of the system, it provides high precision and less computational complexity. The idea compensatory neuron is evolved from a reflex system of the human brain which takes over the control of hazardous conditions [IV]. CNs gets activated when there is a test sample falls in the overlapped regions of different categories and it is able to handle the overlapping of hyperboxes and containment. The following figure shows the architecture of FMCN neural network.
To the input layer, the input vector is given as input and the dimensions of the input layer nodes are equivalent to the dimension of the applied input vector $a_h$, where

Input samples: $a_{h1}, a_{h2}, ..., a_{hn}$
Input nodes: $a_1, a_2, ..., a_n$

Hyperbox nodes: $b_1, b_2, ..., b_j$
Class nodes: $c_1, c_2, ..., c_k$
Overlap compensation hyperbox nodes: $d_1, d_2, ..., d_p$
Containment compensation hyperbox nodes: $e_1, e_2, ..., e_q$
Overall compensation nodes: $o_1, o_2, ..., o_k$

There are three sections of middle and output layer nodes: Classifying Neuron (CLN), Overlap Compensation Neuron (OCN), and Containment Compensation Neuron (CCN). In the middle layer, min-max points $(V, W)$ represents the connections between an input node and a hyperbox node. Overlap represented using hyperbox nodes in OCN and containment is CLN section, respectively. During the training process, middle layer neurons are created.

### III.iv.a Classifying Neurons

In classifying neurons (CLN), if the training sample belongs to a class which has not been met previously or existing hyperboxes of that class cannot be extended anymore to adapt it, then hyperbox nodes are created. The connections between hyperbox and class nodes are represented by matrix $U$ in CLN section. The following equation represents the connection between hyperbox node $b_j$ to a class node $c_i$.

$$ u_{ij} = \begin{cases} 1 & \text{if } b_j \in c_i \\ 0 & \text{if } b_j \notin c_i \end{cases} \quad (41) $$
3.4.2. Overlap Compensation Neurons

Whenever the overlap has been existing, a hyperbox node is created in the middle layer of OCN section. The problems of overlap are taken care of by the OCN section. The connections between hyperbox and class nodes are represented by matrix Y in OCN section. The Overlap between the $i^{th}$ and $j^{th}$class hyperbox represented by the connection weight from neuron $d_p$.

$$y_{ip} \text{and } y_{jp} = \begin{cases} 1, & \text{if } d_p \in c_i \cap c_j, \text{ } i \neq j \\ 0, & \text{otherwise} \end{cases}$$

(42)

3.4.2. Containment Compensation Neurons

Whenever hyperbox of one class is contained fully or partially within a hyperbox of other class, a hyperbox is created in CCN section. The connection between the hyperbox and class nodes is represented by matrix Z in CCN section. In CCN section, connection weights of a neuron are as:

$$z_{iq} = \begin{cases} 1, & \text{if } c_j \text{ is contained fully or partial by } c_i, \text{ } i \neq j \\ 0, & \text{otherwise} \end{cases}$$

(43)

In CLN section, the number of nodes of the output layer is similar to the learned classes. In OCN and CCN section, a number of class nodes rely upon on the overlap network faces nature during the training phase.

IV. Results and Discussion

We measured the performance of the proposed system on the Dresden image database [XX]. The details of used cameras can be found in table 1. The image database as in table 1 is comprised 700 images taken using 7 different cameras. Sample images from this database are shown in figure 3. It is necessary to evaluate the performance of system when manipulated images are used in the experiment. Table 2 shows the manipulation type and the degree of rotation. These manipulated images are included in dataset of training and testing.

| Camera Model    | Resolution | Notations | Number of images |
|-----------------|------------|-----------|-----------------|
| Casio_EX-Z150   | 3,264 × 2,448 | C1        | 100             |
| Kodak_M1063     | 3,664 × 2,748 | K1        | 100             |
| Nikon_D200      | 3,872 × 2,592 | N1        | 100             |
| Nikon_D70       | 3,008 × 2,000 | N2        | 100             |
| Olympus MJU     | 3,648 × 2,736 | O1        | 100             |
| Samsung L74     | 3,072 × 2,304 | S1        | 100             |
| Samsung_NV15    | 3,648 × 2,736 | S2        | 100             |
Figure 3: Sample images of the Dresden Database [XX].

| Manipulation Type | Degree of Rotation |
|-------------------|--------------------|
| Rotation          | $-5^\circ$ | $5^\circ$ | $-10^\circ$ | $10^\circ$ | $-15^\circ$ | $15^\circ$ |

In the first experiment, Gaussian-based denoising filter is used for denoising the images. The histogram of a denoised image of Nikon_D200 using Gaussian filter is shown in figure 4(a). The following measure is to extract the PRNU noise pattern. Following, in feature extraction step, the noise patterns are represented by Krawtchouk Moments. For training and classification, Fuzzy Min-Max Neural Network with Compensatory Neuron (FMCN) is utilized. In the second experiment, Wavelet-based denoising filter is used for denoising the images. The histogram of a denoised image of Nikon_D200 using a Wavelet-based filter is shown in figure 4(b). In the following step, PRNU noise pattern is drawn out. And then, the noise patterns are represented by Krawtchouk Moments. For training and classification, Fuzzy Min-Max Neural Network with Compensatory Neuron (FMCN) is utilized.
Ten-fold cross-validation is applied for measuring the operation of the classifier [X]. In this, the entire data set is split into ten folds, with the end goal that each fold having around one-tenth of the class tests. Prepare entire dataset utilizing Fuzzy Min-Max Neural Network with Compensatory Neuron (FMCN). One fold of the data set is utilized for testing and nine folds are utilized for classification. The normal, recognizing precision is utilized as execution measure and the confusion matrix is utilized to visualize the order result. Table 3 shows the performance evaluation of camera identification using Gaussian and Wavelet-based filter. The TPR values for experiment 1 and 2 for seven camera devices are presented in table 4. Figure 5 presents the comparative graph for different feature-based methods. The recognition accuracy is 93.3% for the first experiment and 98.3% for the second experiment for 7 distinctive cameras.

| Camera Group | Gaussian-based | Wavelet-based |
|--------------|----------------|---------------|
| C1           | 93%            | 100%          |
| K1           | 94%            | 98%           |
| N1           | 92%            | 97%           |
| N2           | 93%            | 94%           |
| O1           | 90%            | 98%           |
| S1           | 93%            | 92%           |
| S2           | 92%            | 93%           |

Table 4: TPR values for experiment 1 and 2 for 7 camera devices.
Figure 5: Comparative graph for different feature based methods

### V. Conclusion

In this paper, the problem of identification of a camera for source image is carried out using a feature based technique. The PRNU noise is extracted from the images utilizing denoising filter and is characterized by Krawtchouk Moments. Then these characteristics are fed to Fuzzy Min-Max Neural Network with Compensatory Neuron (FMCN). The proposed approach is capable of identifying the camera with 93.3% average accuracy for first experiment and 98.3% average accuracy for the second experiment. Likewise, the proposed technique has the ability to identify the cameras capturing the same image and stays powerful regardless of whether the images are subjected to basic manipulations or geometric deviations. By wiping out the effect of the random noise will make further improvement in the outcome.
References

I. Alessandro Piva, “Review Article an Overview on Image Forensics”, Hindawi Publishing Corporation ISRN Signal Processing, Volume 2013, Article ID 496701, http://dx.doi.org/10.1155/2013/496701 (2013)

II. A. Tuama, F. Comby and M. Chaumont, "Camera model identification based machine learning approach with high order statistics features", 24th European Signal Processing Conference (EUSIPCO), Budapest, 2016, pp. 1183-1187.

III. Anass El affar, Khalid Ferdous, AbdeljabbarCherkaoui, Hakim El fadili and Hassan Qidaal, “Krawtchouk Moment Feature Extraction for Neural Arabic Handwritten Words Recognition”, IJCSNS International Journal of Computer Science and Network Security, Vol.9 No.1. 2009.

IV. Abhijeet V. Nandedkar, Prabir K. Biswas, “A Fuzzy Min-Max Neural Network Classifier with Compensatory Neuron Architecture”, IEEE Transactions On Neural Networks, Vol. 18. No. 1, 2007.

V. F. Meng, X. Kong and X. You, A new feature-based method for source camera identification, in Advances in Digital Forensics IV, I. Ray and S. Shenoi (Eds.), Springer, Boston, Massachusetts, pp. 207–218, 2008.

VI. F. Razzazi and A. Seyedabadi, "A robust feature for single image camera identification using local binary patterns," 2014 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), Noida, 2014, pp. 000462-000467.

VII. G. Xu, Y. Q. Shi, "Camera model identification using local binary patterns", Proc. IEEE Int Conference on Multimedia and Expo (ICME), pp. 392-397, 2012.

VIII. I. Amerini, R. Caldelli, P. Crescenzi, A. Del Mastio, A. Marino, “Blind Image Clustering Based on the Normalized Cuts Criterion for Camera Identification”, Image Communication, ELSEVIER, pp. 1 - 13, 2014.

IX. J. Lukas, J. Fridrich and M. Goljan, "Digital camera identification from sensor pattern noise," in IEEE Transactions on Information Forensics and Security, vol. 1, no. 2, pp. 205-214, June 2006.

X. K.R. Akshatha, A.K. Karumakar, H. Anitha, U. Raghavendra, Dinesh Shetty, “Digital camera identification using PRNU: A feature based approach”, Digital Investigation, Journal, Elsevier, 19 (2016)

XI. M. C. Stamm, M. Wu and K. J. R. Liu, "Information Forensics: An Overview of the First Decade", in IEEE Access, vol. 1, pp. 167-200, 2013.

XII. M. Kharrazi, H.T. Sencar, N. Memon, "Blind source camera identification”, IEEE International Conference on Image Processing ICIP '04., vol. 1, pp. 709-712, 2004.
XIII. M. KivancMihcak, I. Kozintsev and K. Ramchandran, "Spatially adaptive statistical modeling of wavelet image coefficients and its application to denoising," 1999 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings. ICASSP99 (Cat. No.99CH36258), Phoenix, AZ, 1999, pp. 3253-3256 vol.6.

XIV. O. Celiktutan, B. Sankur, I. Avcibas, "Blind identification of source cell-phone model", IEEE Transactions on Information Forensics and Security, vol. 3, no. 3, pp. 553-566, 2008.

XV. P. T. Yap, P. Raveendran and S. H. Ong, “Krawtchouk moments as a new set of discrete orthogonal moments for image reconstruction”, In Neural Networks, 2002. IJCNN’02. Proceedings of the 2002 International Joint Conference on (Vol. 1, pp. 908-912). IEEE, 2002.

XVI. P. T. Yap, R. Paramesran and S. H. Ong, “Image analysis by Krawtchouk moments”, Image Processing, IEEE Transactions on, 12(11), 1367-1377, 2003.

XVII. S. Bayram, H.T. Sencar, N. Memon, "Improvements on source camera model identification based on cfa interpolation", Advances in Digital Forensics II IFIP International Conference on Digital Forensics, pp. 289-299, 2006.

XVIII. S. Saito, Y. Tomioka and H. Kitazawa, "A Theoretical Framework for Estimating False Acceptance Rate of PRNU-Based Camera Identification," in IEEE Transactions on Information Forensics and Security, vol. 12, no. 9, pp. 2026-2035, Sept. 2017.

XIX. T. Filler, J. Fridrich, M. Goljan, "Using sensor pattern noise for camera model identification", Proc. FCIP 15th IEEE International Conference on Image Processing, pp. 1296-1299, 2008.

XX. TechnischeUniversität Dresden, Dresden, Germany. Dresden Image Database, accessed on May 1, 2015. [Online]. Available: http://forensics.inf.tu-dresden.de/ddimgdb

XXI. X. Kang, Y. Li, Z. Qu and J. Huang, "Enhancing Source Camera Identification Performance with a Camera Reference Phase Sensor Pattern Noise", in IEEE Transactions on Information Forensics and Security, vol. 7, no. 2, pp. 393-402, April 2012.

XXII. Y. Sutcu, S. Bayram, H. T. Sencar and N. Memon, "Improvements on Sensor Noise Based Source Camera Identification," 2007 IEEE International Conference on Multimedia and Expo, Beijing, 2007, pp. 24-27.

XXIII. Yoichi Tomioka, Yuya Ito, and Hitoshi Kitazawa, “Robust Digital Camera Identification Based on Pairwise Magnitude Relations of Clustered Sensor Pattern Noise", IEEE Transactions on Information Forensics and Security, Vol. 8, No. 12, December 2013.