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Literature Survey on Various Source Camera Identification Techniques

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Abstract
The increasing occurrence of digital images in various domains like social media, journalism, and law enforcement has created a need for secure methods to verify their originality and determine their source. Images can easily be manipulated thereby leading to misinformation and other serious consequences. This opens the gateway for different source camera identification techniques like Photo Response Non-Uniformity (PRNU) analysis, Colour Filter Array (CFA) interpolation, Auto-white balance (AWB) approximation, lens radial distortion, and many more. Factors like image type, JPEG compression level, rotation and gamma correction affect the accuracy and reliability of these methods. Henceforth, this paper aims to systematically review source camera identification techniques, detailing their accuracy and applicability across different datasets and camera models.

Keywords: *Color Filter Array, Digital Image, Image Forensics, Photo Response Non-Uniformity, Source Camera Identification.*

1. Introduction

In today's digital era, millions of photos are captured, transmitted, and saved daily, most of which are used in sensitive applications. Source Camera Identification (SCI) aims to determine the origin of an image by correctly identifying the camera or device model used to capture it. By analyzing the important characteristics that are embedded in an image, researchers can utilize them to ensure authenticity and accountability in a wide range of applications. SCI follows a structured process depicted in the following steps,

- Image acquisition (Input Image) - Image is obtained from a camera which can be raw or in compressed formats like JPEG or PNG.
- Preprocessing - Techniques like resizing, converting to grayscale or normalization are applied if required.
- Feature Extraction - Unique features like PRNU, CFA etc., are extracted from the image.
- Feature Matching and Classification - The extracted features are compared against a known database of camera fingerprints.
- Decision and Interpretation (Output Source Image) - The system decides the source of the image in the form of probability or confidence scores.

The above architecture is depicted in Figure 1.

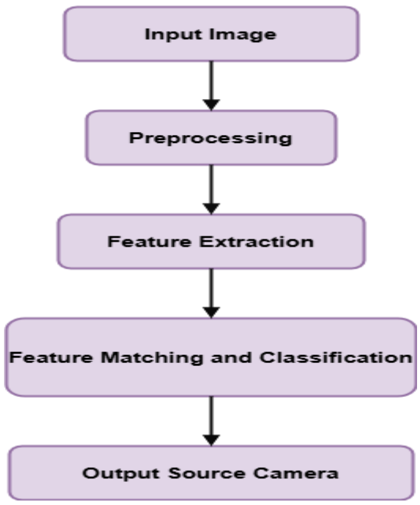

Figure 1 SCI Architecture

2. Image Source Camera Identification Techniques

This section comprehensively reviews different SCI techniques based on both hardware artefacts and software-related properties. Intrinsic hardware flaws include sensor pattern noise (SPN), and lens radial

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distortion, while software-related methodologies include AWB approximation and machine learning [2]. Figure 2 shows the different image SCI techniques.

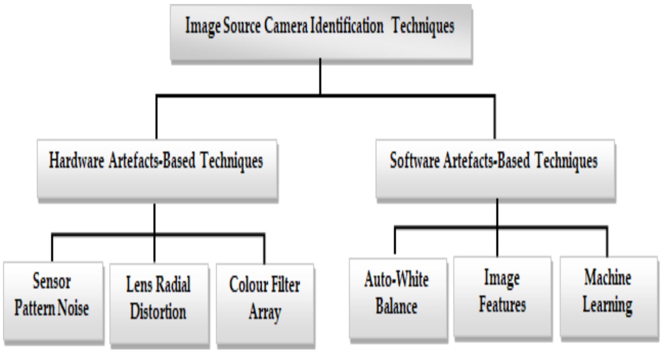

Figure 2 Taxonomy of image SCI techniques [2]

2.1. SPN Based Techniques

In manufacturing an image sensor chip, a flaw would create pixel sensitivity variation in the imaging sensor, which is the source of SPN. These pattern noises make them identifiable to that camera imaging sensor. This provides a ‘fingerprint’ of that particular digital camera. PRNU noise is the major component of SPN [2] and is considered the most reliable technique for SCI. PRNU is subtle and needs specialized algorithms for accurate extraction. This process typically requires averaging multiple images from the same camera to suppress random noise and emphasize the consistent PRNU pattern.

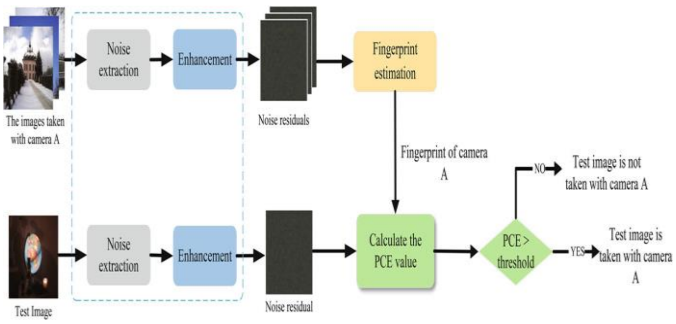

Figure 3 SCI based on PRNU Analysis [9]

Once estimated, the PRNU noise pattern is extracted and represented as a matrix or a set of features. The extracted pattern is then compared against a database of known camera fingerprints, where a high correlation or similarity indicates a match, helping to identify the source camera. Figure 3 represents the PRNU analysis.

2.2. Lens Radial Distortion

The symmetric distortion caused by flaws in the lens’s curvature during the grinding process is known as radial lens distortion [2]. This distortion arises from the geometry of the lens system and is most noticeable in wide-angle and fisheye lenses. It occurs in two forms namely Barrel distortion and Pincushion distortion. Barrel distortion is one where a straight line appears to bulge outward, resembling the shape of a barrel while Pincushion distortion is one where a straight line appears to pinch inward toward the centre, resembling the shape of a pincushion. Figure 4 shows how an original image is converted to depict Barrel and Pincushion distortion.

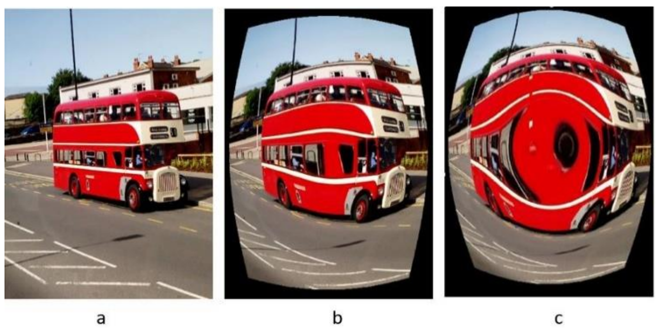

Figure 4 Sample of Lens Radial Distortion (a) Original, (b) Barrel Distortion, (c) Pincushion Distortion [2]

2.3. CFA Interpolation

Digital cameras use CFA to capture colour information. The CFA consists of a mosaic of tiny filters (typically red, green, and blue) placed over the sensor pixels. Each pixel captures only one colour component. The missing colour information for each pixel is then estimated based on the values of neighboring pixels. The algorithm begins by detecting the specific CFA pattern used by the camera, as different manufacturers employ distinct CFA arrangements. It then analyzes the interpolation process, which estimates missing colour values, leaving unique traces based on the algorithm used. Next, relevant features related to the CFA pattern and interpolation method are extracted. Finally, these features are compared against known CFA and interpolation characteristics of various cameras to

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determine the source camera accurately. Figure 5 shows a CFA pattern using CMYK and RGB values.

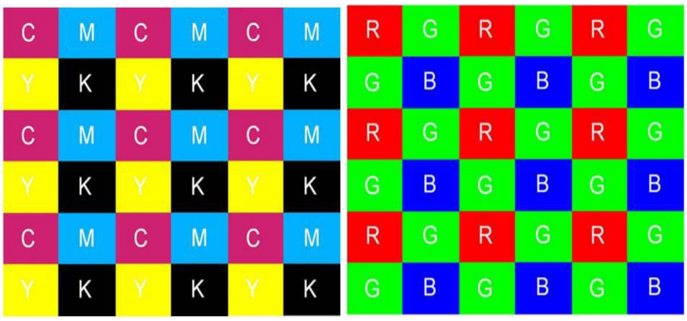

Figure 5 CFA Pattern using CMYK Values and RGB Values [2]

2.4. Machine Learning (ML) and Deep Learning (DL) Algorithms

Apart from PRNU noise and other features, ML algorithms are capable of extracting features like wavelet coefficients, noise residuals and colour artefacts. Some of the commonly used ML classifiers include Support Vector Machine (SVM), Random Forest (RF) and K-nearest neighbours (KNN). On the other hand, DL models can learn complex patterns from images. One such DL model is Convolutional Neural Networks (CNN). CNNs learn spatial hierarchies in image data, making them effective for SCI. Pretrained architectures like ResNet and VGG can be fine-tuned for camera identification.

2.5. AWB Approximation

White balance corrects colour casts in images by adjusting the colour temperature to achieve neutral whites. Ideally, applying the same AWB method repeatedly should yield consistent results termed as idempotence. The original image is resampled and various AWB is applied to approximate the technique that might be used inside the camera. Image features are extracted and feature vectors are selected using sequential backward feature selection and the prediction of the source camera is achieved using an SVM classifier [2].

3. Literature Survey

Jian Li et.al [1] proposed a technique using Principal Component Analysis (PCA) to reduce interference noise within the extracted PRNU. This involved selecting similar local pixel areas and applying PCA to estimate and subtract the interference, leading to a more reliable PRNU for camera identification. This research used the Vision and Dresden datasets. The proposed method achieved Area Under the ROC curve (AUC) values of 0.983 for image sizes of 512x512 pixels. But the running time increases significantly for large image block sizes of 1024x1024. Chijioke Emeka Nwokeji et.al [2] presented techniques for SCI of digital images using hardware and software artefacts for forensic investigations. This paper utilized the Vision, Dresden, and high dynamic range image datasets. This survey proved that SPN achieved the best accuracy of 99.8% and that the performance of some methods is affected by image content and some techniques can be computationally expensive. Manisha et.al [3] proposed a novel approach combining a ResNet101 and an SVM on downsampled and randomly sampled images to extract and verify the device-specific fingerprint. Experiments conducted demonstrated that this new fingerprint is highly resilient to image manipulations such as rotation, gamma correction, and aggressive JPEG compression. This approach achieved an accuracy of 96.02% on the UNISA2020 dataset. Joshua Olaniyi-Ibiloye et.al [4] explored the correlation between the Polluted Photo Response Non-Uniformity (POL-PRNU) from random images in a dataset to create clusters such that, each cluster would represent images most likely taken by the same camera. The dataset included 15 images each from 3 camera models namely Nikon D1500, Nikon D1200 and Canon EOS 1200D but achieved a low accuracy of 46%. P Shashank Kumar et.al [5] used PRNU to analyze visual noise patterns and compare them with CNN's expertise in eliminating distinguishing elements to determine the source of an image. Results from the experiments highlight that the integration of PRNU and CNNs achieved an accuracy rate of 89.47% on the CIFAR-10 dataset. This integrated approach proves beneficial across various forensic applications. Due to the inherent characteristics of the gadget used in the study, certain limitations occur. Shimji K et.al [6] proposed a method where a fingerprint is extracted using a weighted combination of two types of de-noising filters, weighted nuclear norm minimization (WNNM) based filter and wavelet

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filter. After extraction, the fingerprints were clustered using correlation clustering followed by consensus clustering and final refinement based on their origin. A set of images captured by different mobile cameras at various locations were used as datasets. A total of 3 datasets were employed out of which Dataset 2 (D2) achieved the highest accuracy of 97.9% respectively. Vittoria Bruni et.al [7] proposed a method that leveraged the coherence between different PRNU estimations across specific image regions to improve the accuracy and reliability of SCI. Dresden and Vision datasets were used where the natural images from the Dresden dataset achieved an accuracy of 99.18% at a fixed sensitivity value of 0.6809. One disadvantage of this method is its dependence on the accuracy of the denoising filter, as residual edges from imperfect denoising can lead to misclassifications. Nili Tian et.al [8] proposed an improved PRNU noise extraction model utilizing a noise extractor combining Generalized Anscombe Transform (GAT) and adaptive block clustering PCA filtering, followed by a noise enhancement algorithm with Real-Imaginary Separation Smoothing (RISS) based on half-quadratic optimization and Cyclic Residual Recycling (CRR). The model was evaluated on the Dresden Image Database and achieved a Kappa coefficient of 0.9884 for the 512x512 resolution category. One drawback of this model is its relatively longer execution time compared to some other methods. The authors attribute this primarily to the time-intensive clustering process in noise extraction and the repeated application of iterative least squares in CRR. Hui Zeng et.al [9] provided a comparison of using CNN-based denoisers for PRNU extraction. The study compared 4 CNN denoisers namely DnCNN, FFDNet, ADNet, and DANet with traditional denoising filters on the Dresden Image Database. Among these, ADNet achieved an AUC value of 0.963 in the ROC curve analysis. The downside of this method is that when training with image-PRNU pairs, it may also increase false alarms in SCI by enlarging the range of metrics for negative samples. Abdul Muntakim Rafi et.al [10] introduced RemNet, a novel CNN architecture that employs learnable "remnant blocks" that adaptively suppress irrelevant image details while enhancing features useful for identifying the camera model. RemNet consists of a preprocessing block and a shallow classification block that achieved a 100% accuracy on the Dresden image database and an overall accuracy of 95.11% on the IEEE Signal Processing Cup 2018 dataset. Determining the optimal number of remnant blocks, the depth of each block, the number of filters in each layer, and the kernel sizes require cross-validation, which can be computationally expensive and time-consuming. Yuan- yuan Liu et.al [11] proposed a CNN to extract image color correction features and identify and classify source camera models. This method achieved an accuracy of 97.23% while the recognition accuracy under compression conditions reached 91.28%. A custom dataset was used which included colour checker images, original images and Facebook compressed images. However, this method only considers extraction of the camera colour correction matrix (CCM) features under the same lighting condition at the same time. Changhui You et.al [12] proposed MCIFFN, a multiscale feature fusion network for source camera identification. It suppresses image content by extracting and fusing camera attribute noise using dual filter sizes and identity mapping. Multiple CNNs extract diverse features, which are fused and refined for optimal selection. This method was applied to the Dresden database and achieved an accuracy of 98.51%. Despite significant improvements in speed and accuracy, the algorithm still falls short of meeting engineering requirements for model size and execution speed. Guru Swaroop Bennabhaktula et.al [13] proposed a new approach that leverages the homogeneous regions in given images, which are less distorted by the scene content, for reliable extraction of forensic traces. It showed that when such input data is trained in a hierarchical classification approach with CNN as the base model, it results in a computationally efficient classifier than a flat (single classifier) approach. This method achieved an accuracy of 99.01% for the ‘natural’ subset of the benchmark Dresden dataset of 18 camera models. Chen Chen et. al [14] designed a multi-class ensemble classifier to utilize all extracted color value correlations to perform camera model identification. This model achieved an accuracy of 98.14% on a

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custom database with 68 camera models and is highly robust to post-JPEG compression and contrast enhancement. Sidra Naveed Mufti et.al [15] proposed an algorithm that estimates the camera fingerprints from the images and clusters them in two stages namely, initial clustering and fine clustering, with additional processes of resizing, standardization and merging. The algorithm was tested on the Dresden dataset and achieved a precision of 0.985, shown in Table 1.

Table 1 Comparison of Various Face Recognition Approaches

Method	Database	Evaluation Metric	Author	Year
PCA-based interference [1]	Vision, Dresden	AUC = 0.983 (512x512)	Jian Li et.al	2023
SCI using hardware & software artefacts [2]	Vision, Dresden, and high dynamic range	Accuracy = 99.8% (SPN)	Chijioke Emeka Nwokeji et.al	2024
ResNet101 + SVM [3]	UNISA2020	Accuracy = 96.02%	Manisha et.al	2022
POL-PRNU clustering [4]	Custom dataset (NikonD1500, Nikon D1200 and Canon EOS 1200D)	Accuracy = 46%	Joshua Olaniyi-Ibiloye et.al	2023
PRNU + CNN [5]	CIFAR-10	Accuracy = 89.47%	P Shashank Kumar et.al	2023
WNNM & wavelet filter-based fingerprint clustering [6]	D2(Huawei-P9, Galaxy-Note5, OnePlus-3t, iPad-Air and iphone se)	Accuracy = 97.9%	Shimji K et.al	2021
PRNU coherence across image regions [7]	Vision, Dresden	Accuracy = 99.18%	Vittoria Bruni et.al	2021
GAT, PCA and RISS [8]	Dresden	Kappa = 0.9884 (512x512)	Nili Tian et. al	2024
CNN Denoisers (DnCNN, FFDNet, ADNet, DANet) [9]	Dresden	AUC = 0.963 (ADNet)	Hui Zeng et.al	2021
RemNet [10]	Dresden and IEEE Signal Processing Cup 2018	Accuracy = 100% (Dresden) Accuracy = 95.11% (IEEE Signal Processing Cup 2018)	Abdul Muntakim Rafi et.al	2021
CNN [11]	Custom dataset (colour checker images, original images, Facebook compressed images)	Accuracy = 91.28% (compressed conditions)	Yuan- yuan Liu et.al	2023
MCIFFN + CNN [12]	Dresden	Accuracy = 98.51%	Changhui You et.al	2021

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Hierarchical classification approach with CNN [13]	Dresden (natural images)	Accuracy = 99.01%	Guru Swaroop Bennabhaktula et.al	2022
Multi-class ensemble classifier [14]	Custom dataset of 68 camera models	Accuracy = 98.14%	Chen Chen et. al	2021
Two-stage clustering algorithm [15]	Dresden	Precision = 0.985	Sidra Naveed Mufti et.al	2022

Conclusion

The field of digital forensics and other domains can be enhanced by exploring and optimizing techniques for identifying the source camera of an image. This can yield good results even under challenging conditions like compression, transformations and dataset diversity. This paper provides an overview of different SCI techniques available that are employed against different datasets showcasing their accuracy and specific camera models. Further, focusing on improving generalization across different conditions and boosting computational efficiency can help develop countermeasures against malicious attacks.

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