Source Camera Identification for Mobile Phones using EXIF Data and Lens Features

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***Abstract*—Source camera identification is the process of discerning which camera has been used to capture a particular image. This study has focused on analyzing the relationship between mobile enabled cameras and the photographs. Mobile cameras are typically low-end cameras equipped on hand-held devices such as personal digital assistants and cellular phones. The fast proliferation of these mobile cameras has brought up concerns on the origin and integrity of their output images. In this paper, we try to identify the source mobile cameras by combining some features extracted from a test image especially some unique features like focal length, aperture value of the lens, resolution etc. The technique focuses on identifying some features that can differentiate the characteristic quality and size trade-off among different camera models. Simulation is carried out to evaluate the success rate of method.**

***Keywords*—** *Mobile Phones, Image forensics, Image Classification, Lens Characteristics*

1. INTRODUCTION

With the increasing popularity of cell phones equipped with camera in recent years, so does the need to accurately identify the source cell phone of a given digital image. In the forensic context, the wide-scale availability of cellular-phone cameras will signify that there will be increasingly more evidence in the form of cell-phone images brought to courts or reported to law-enforcement officers.

The downside of it is that cell-phone cameras can also be used for criminal purposes, such as pilfering credit-card information and child pornography. Therefore, the identification and verification of source cameras has become necessary for legal purposes and security investigations. Multimedia forensics uses multimedia objects to trace back to the original digital device which created the objects. This kind of identification would be useful in legal disputes such as claiming of multimedia assets ownership, and more Importantly, being used as digital evidence in the court. The camera identification problem can be addressed within the frame- work of image forensics.

Image forensics is an emerging field concerned with determining the source and potential authenticity of digital objects and possibly reconstructing the history of manipulations effected. An obvious threat to image authenticity is the ease with which digital images can be created, edited, and manipulated with sophisticated tools which do not leave much perceptible trace [1]. A second important threat is the obfuscation of the source identity of the imaging device. In this respect, the image header, where such information as camera brand, model, date, and time, etc., are embedded is no longer reliable. Also, there are currently a limited number of source camera identification methods. These methods explore different parts or processing stages of the digital camera to find the clues that can help identifying correctly the source camera.

In this paper, we exploit the fact that most consumer level camera enabled mobiles employ different and distinct features which when recognized and analyzed correctly will lead us to the correct source of the image... The trade-off between size and quality varies from one camera to another. If we can find out some features to characterize this trade-off, it is possible to classify images originating from a number of cameras by this method. Our technique works in the direction to identify the source of the image, thus we also tried to find some unique characteristics and patterns produced by a particular mobile enabled camera and personal digital assistance. We use these unique characteristics into an instance based k-NN algorithm [10] that is widely used for classification and regression during cluster analysis and pattern recognition. Some of the features that are unique for all the cameras is the focal length of the lens, also the aperture value and most importantly the resolution index of the image. Our technique also emphasis on ELA i.e. Error Level Analysis [11] It is an analysis to identify digital modification and changes applied to the image when the error level significantly varies from the original image.
This paper is organized as follows. In Section II, we first give

a review of the related work already done in this field. Section III gives the overview of the Error Level Analysis and the features proposed to characterize the quality and size trade-off of a camera. Also, focal length and aperture value of the lens have been reviewed in the same section. The methodology of the experiment done has been explained in section 4. Experimental results for a various camera case are

Provided in Section 5. The conclusion is presented in Section 6.

2. BACKGROUND AND RELATED WORK

There have been number of studies in the literature for camera identification based on the exploitation of residual artifacts and imperfections in the imaging pipeline. We can divide these approaches into two main groups according to the information source they use. The methods in the first group use sensor noise and artifacts in the CCD array. The second group approaches camera identification via demosaicing artifacts taking place in the processing of raw sensor images. Camera identification based on sensor noise: Geradts et al. [2] observed that large CCD arrays of- ten contain a variety of manufacturing defects, such as hot point defects, dead pixels, pixel traps, and cluster defects, which, in total, amount to fixed pattern noise. In addition, camera electronics in the camera generate random dark current. They have observed that while dark current has limited potential in building a forensic signature, the fixed pattern noise of the CCD array is instrumental in constructing a unique pattern for each camera.

Kurosawa et al. [3] and Lukas et al. [4] also turned their attention to the pattern noise of CCD arrays. Lukas et al. found that the systematic part of the noise does not change much from image to image, is relatively stable over camera life span and operating conditions, and consists of the fixed pattern noise plus photo-response non-uniformity artifacts. While the fixed pattern noise can be corrected for by subtraction of a dark frame, the photo response non-uniformity noise (PRNU) caused by pixel non-uniformities is a more persistent feature. The PRNU can be reliably extracted by averaging the de-noising residuals of several images. This signal pattern plays the role of a signature, that is, it acts like a spread-spectrum watermark unique to each camera.

Camera identification based on demosaicing artifacts: Commercial imaging devices use a single mosaic structured CFA rather than having separate filters for each color component. Camera models employ their proprietary interpolation algorithm in recreating the missing color values [5]. The grid interpolation process, in turn, leaves footprints, such as correlation patterns between contiguous bit planes. Kharazzi et al. [6] tried to capture the differences in CFA configuration and color-processing pipeline by a feature-based approach. They focused on features, such as mean value of RGB channels, correlations between color components, differences in neighborhood distribution, wavelet-domain statistics [7] and image-quality measures. Since the residuals of interpolation algorithms depend on the nature of the captured content, these authors fine-tuned their algorithm by separately treating the smooth and non-smooth parts of the images.

In another study, Long and Huang [8] used intermixed correlations originating from demos icing. They defined a quadratic pixel correlation model and obtained a coefficient matrix for each color band based on this model. Swami Nathan et al. [9] investigated the demosaicing artifacts using an analysis-by-synthesis method. They divided the image into three regions based on gradient features in a local neighborhood and then they estimated interpolation coefficients through singular value decomposition (SVD) for each region and each color band separately. Then, they re-interpolated the sampled CFA pattern and chose the one that minimizes the difference between the estimated final image and actual image produced by the camera.

Camera identification by alternative methods: In [8], the authors used intrinsic lens radial distortion for camera identification. The underlying idea is that most of the digital cameras are equipped with lenses having spherical surfaces and the degree of their inherent radial distortions varies from one manufacturer to another. However, the lens features have not proven to be robust since the distortion parameters are influenced by the focal length of the lens. Another method is the use of sensor dust characteristics of digital single-lens reflex (DSLR) cameras [10]. When the interchangeable lens is removed, dust particles are attracted to the sensor and they create a dust pattern in front of the imaging sensor. This dust pattern may be fairly stable on the sensor surface since most digital cameras do not offer a built-in solution for sensor dust removal.

3. THE TECHNIQUES

This section discuss about the two algorithms which we have used to identify the source of the image. Let's discuss the technique in detail-

3.1. k-NN algorithm

k-NN or k- Nearest Neighbor Algorithm [11] is an instance based algorithm which comes under lazy learning where the function is only approximated locally and all computation is deferred under classification. There are two categories of k-NN algorithm i.e. weighted and un-weighted. Weighted k-NN algorithm is also called as Single Feature Accuracy and is defined as weight of the feature as the accuracy obtained by feature alone. It's a non-incremental i.e. all instances are taken and processed as one. In order to classify an instance, a pre-classification separately on each feature is performed. In this we use the algorithm for single dimension that is for k-1 will be the class for training instance. For a larger value of k, the pre-classification is a bag of classes of the nearest k training instances.

For k=1, the accuracy level is on the higher side as compared to higher values of k as each feature has k votes and as k increases so will be the majority but k-NN also works on the distance between two instances, but here majority will overshadow the distance.

k-NN algorithm usually uses Eucledian Distance for the calculation of the distance between two neighbors. Eucledian distance plays a very important role in maintaining the accuracy of the algorithm. k-NN algorithm can be used for both classification and regression, in classification object is classified as majority of votes of its neighbors and in regression it is the average of the value of its neighbors

3.2. ERROR LEVEL ANALYSIS

ELA (Error Level Analysis), it primarily defines the area within the image that are at different compression levels. This technique is used whenever there is modification of the digital data, in this the changes are highlighted by varying the color brightness to a higher level with respect to the image. It actually works by re-saving the image at a known rate and then comparing it with the original image, if there is no change in the image then the pixels have reached its local minima for error at a quality level and if there is a change then the pixels have not reached its local minima, so the image is effectively original. ELA highlights the differences that occur in JPEG compression. The JPEG(Joint Photographic Experts Group) 2000 standard, finalized in 2001, defines a new image-coding scheme using state-of-the-art compression techniques based on wavelet technology. Its architecture is useful for many diverse applications, including Internet image distribution, security systems, digital photography, and medical imaging. Nowadays, JPEG compression is used standard stage in the camera pipeline in most consumer-level camera enabled mobile phones. As ELA highlights the differences in JPEG compression so the regions with uniform coloring will have a lower ELA. In ELA there are three factors to look for-

1. Edges-Similar Edges would have similar brightness in the result so given an original photo, our first job would be to look at the edges and if there is a difference in the brightness level after compression.

2. Textures- Alike edges, images with similar texture will have similar ELA.

3. Surfaces- All surfaces should have the same color under ELA.

In ELA, we look around the image surfaces and textures for high-low contrast/ brightness areas that might lead us to find out the modifications in the image. Re-saving an image leads to removal of high frequencies so the difference in surfaces with suspicious high contrasts reduces. But scaling a picture smaller can boost the high contrast edges, making the brighter under ELA, as similarly in Adobe products automatically sharpens high contrast edges making them appear brighter.

4. FEATURE SET

Feature selection is the most critical part of any classification, clustering process. Below mentioned is the list of features which have been considered for evaluation purpose in our study. Our goal is to find out those unique feature for all the mobile phone cameras we have taken into consideration and find that if it may lead to some unique patterns that can be used for identifying the source for any image along with machine learning using k-NN algorithm and Error Level Analysis.

4.1. Focal Length and Aperture Value of Lens

The Focal Length of an optical system is a measureof how strongly the system converges (focuses) or diverges (defocuses) light. For an optical system in air, it is the distance over which initially collimated rays are brought to a focus. A system with a shorter focal length has greater optical power than one with a long focal length; that is, it bends the rays more strongly, bringing them to a focus in a shorter distance.

Lens aperture is found on the camera lens, and it determines the amount of light that passes through the lens opening and onto the digital sensor or photographic film. This is done by changing the size of the aperture opening on the lens, much like the eye pupils contract and expand to let more or less light in.

4.2. Resolution for *the Camera*

As phone cameras are defined with a particular mega pixel, every mega pixel is defined with a particular resolution range so for a definite camera mega pixels there will be definite range for its resolution (e.g. 5 mega pixel cameras have a maximum resolution of 2592*1944). Table I. Shows relation between maximum resolution and mega pixels.

Maximum Resolution	Mega Pixels
640*480	0.3
1280*960	1
1600*1200	2
2560*1920	5
3264*2448	8
4128*3096	13

Table I. Maximum Resolution vs Mega Pixels

4.3. *Mega pixels of a Camera*

As every phone is built with a camera of a particular mega pixel but irrespective of that a phone can capture an image with lower mega pixels as well so thereby giving us a minimum and maximum value of mega pixel range.

4.4. F-number-

It is the ratio of the Len's\ focal length to the entrance pupil. It is a quantitative measure of Len's speed, also an important part of photography
Depth of the field increases with f-number, thus a low f-number means an object is in focus.

4.5. Exposure Value

Exposure Value is a characteristic feature which defines how light or dark an image will be. It is dependent upon ISO speed, Shutter Speed and aperture.

4.6. DPI (Dots per Inch)

DPI is the measure of dots available per inch. It is a measure of how an image is printed on a medium.

4.7. Image Size- Depending upon the mega pixels of the camera and resolution, the image size will vary. So we have used this parameter to define a maximum and minimum size by a specific mega pixel camera.. E.g. If an image is clicked with maximum zoom, the image size will be minimum.

4.8. Attribute Factor- This is also a feature that distinguishes the camera as it can only be of two types- 'A' or 'N'. The major significance of this feature is that every cropped images has an attribute 'A' so it also helps in Error Level Analysis.

Our goal is to find the unique patterns for all the cameras we have taken into consideration and find that if we could lead to some unique patterns for each of them so that we can identify the source camera for any image along with Error Level Analysis and Machine learning using k-NN algorithm.

5. METHODOLOGY

A mobile camera may have more than one JPEG quality setting and also its pixel dimension can change. Each quality setting has a specific trade-off between size and quality. With a limited number of camera models, the characteristics of the JPEG quality settings and other lens features which we have included in our study like lens focal length, aperture value may be distinctive. As a consequence, we can identify the JPEG quality setting of an image and these lens features, hence the source camera of the image.

The implementation of our method comprises of following subunits-

5.1 Data Preparation- The phase of the implementation starts with preparing the data first. So for this we collected 13 different phones of different brands and models. We took 6 objects and took 20 images from each phone of each object. These images were taken under different modes such as black and white, auto focus, sepia, night mode, landscape, no manual zooming, and at different ISO speed, shutter speed, and even at different mega pixel range. Maximum optical zoomed in image was also taken in order to determine the minimum Image size. This was done to come up with a heuristic, that if we can come up with an efficient classification method.

5.2 Image Collection and Compilation- After the completion of data preparation, the next phase was Systematic Image Collection and Compilation, so for this we made a database of these collected images with respect to the mobile phone used. We categorized our images and also made a database of metadata that we got after passing the image on our Exif Viewer

5.3 Factors Identification and Feature Set-Now after the Image collection and compilation and also the collection of metadata of all the images in our database, we moved on to find the features that our distinct among different phones but similar in the images of the same phone. In order to this we also took care of the features that can be easily modified using editing software and by changing the settings, these features were ISO speed, time, white balance, etc. So we didn't include these features in our feature set. There were feature which can't be modified in an image, these were *focal length, aperture value, horizontal and vertical Dpi, mega pixels, exposure, attribute factor.*

5.4. Machine learning with k-NN Algorithm- After the completion of the feature set, a CSV (Comma Delimited) file was made and was uploaded on Weka Machine Learning Tool where we did the classification of our feature set using k-NN algorithm and then analysis of visualization plot.

5.5. Error Level Analysis- We used this additional technique to find out if the image is modified or edited with any additional object, we did this by re-saving the image at a 95% quality and analyzed this image and the original one. We examined it in the gray scale mode and if there was any changes then the modified part was brighter than the original. So we can remove that part and then again repeat our process of collection of Meta Data.

The mobile phones that are used are shown in Table I. Figure 2 presents some of the samples from our image data set. After collecting the data set, the proposed measures have been calculated for each image.

Sr.no.	Company	Mobile Model
1.	Nokia	520
2.	Nokia	710
3.	Samsung	Grand GT-1908
4.	Samsung	GT-C3322
5.	Samsung	Galaxy S-Duos
6.	Samsung	Galaxy-S3
7.	Samsung	Galaxy-SL
8.	Black Berry	9220
9.	Micromax	A110
10.	Apple	Iphone 4s
11.	HTC	One-X
12.	Sony	Xperia-Zr
13.	LG	G2

Table II. Phone Models

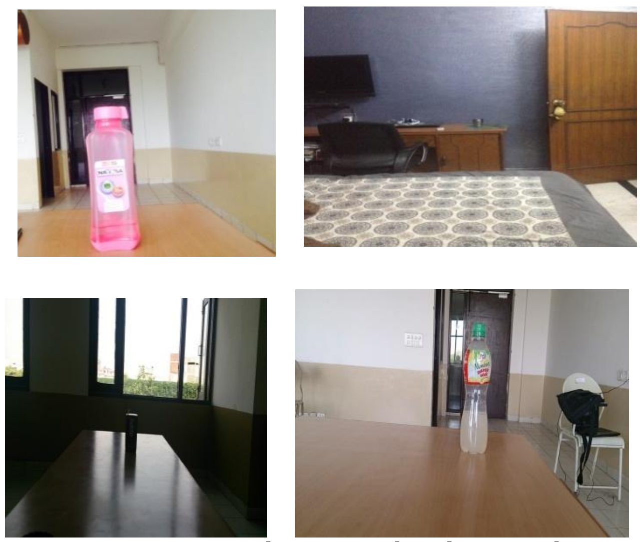

Figure I. Sample Images taken during study

6.ANALYSIS AND RESULTS

The above section describes the methodology by which we collected the data for the analysis, here in this section we have done the analysis of that data and come up few interesting and eye opening results later. The steps are as follows:

1. As we had created a feature set so we completed the feature set with all the attributes of all 13 phones.
2. A CSV file was made which was uploaded for training purpose on Weka.
3. Classification was used with the help of k-NN algorithm.

Table III and IV show the out comes from the Exif reader that include the focal length of the lens, its aperture value and all other features for particular mobile phone camera. We can see that if we combine all these characteristics for a particular mobile phone then we get a unique pattern.

Table III Feature Set-1

Phones	Megapixel	FileMinsize	File-Maxsize	Aperture	Focal Length
Samsung Galaxy SL	5	439	1264	2.6	3.4
Sony Xperia Zr	13.1	359	2539	2.4	4.1
Nokia Lumia 520	5	662	1172	2.4	2.4
Htc One X	8	818	1670	2	3.6
Samsung Galaxy S3	8	911	1567	2.6	3.7
Nokia Lumia 710	5	561	872	2.6	2.4
Samsung GT C3322	1.3	253	375	2.6	2.8
Apple Iphone 4s	8	1190	3508	2.6	4.3
Samsung Galaxy S Duos	5	883	1450	2.6	3.5
Black Berry 9220	1.3	301	421	2.6	2.5
Micromax A110	8	613	2736	2.4	4
Samsung Grand GT-1908	8	600	2000	2.6	3.7
LG- G2	13	1860	2070	2.6	3.97

Phones	Resolution		F-no.	Dpi	Attribute	Exposure
Samsung Galaxy SL	2592*1944		2.6	72	N	0.03
Sony Xperia Zr	4128*3096		2.4	72	N	0.02
Nokia Lumia 520	2592*1944		2.4	72	N	0.02
Htc One X	3264*2488		2	72	N	0.03
Samsung Galaxy S3	3264*2488		2.6	96	A	0.03
Nokia Lumia 710	2592*1944		2.4	72	A	0.04
Samsung GT C3222	1600*1200		2.8	96	N	0.02
Apple Iphone 4s	3264*2488		2.4	72	A	0.059
Samsung Galaxy S Duos	2592*1944		2.6	96	A	0.03
Black Berry 9220	1600*1200		2.5	72	A	0.02
Micromax A110	3264*2488		2.4	72	A	0.043
Samsung Grand GT-1908	3264*2488		2.6	96	A	0.059
LG-G2	4128*3096		2.4	96	N	0.83

Table IV Feature Set-2

Tested Feature	Tested Feature Value	Probable Phones
1.Megapixel	5 mp	Lumia 520,Galaxy SL,Lumia 710, Galaxy S Duos
2.File Size	1140 Kb	Galaxy SL,Xperia Zr,Lumia 520, One X, Galaxy S3, I phone 4s, Galaxy S Duos, G2
3.Aperture	2.4	Xperia Zr,Lumia 520, Lumia 710
4.Focal Length	2.4mm	Lumia 520,Lumia 710
5. Resolution	2592*1944	Lumia 520,Galaxy SL,Lumia 710, Galaxy S Duos
6.F. Number	2.4	Xperia Zr,Lumia 520, Lumia 710, Iphone 4s, A110,G2
7. Dpi	72	Lumia 520, Galaxy SL, Xperia Zr,One X, Lumia 710, Iphone 4s, BB 9220
8. Attribute	N	Galaxy SL,Xperia Zr, One X, C322, G2
9. Exposure	1/50	BB 9220, Xperia Zr, Lumia 520, C322

Table V. Probable phone models for the image about which information is known

Phones	Number of Occurrences	Percentage
1. Galaxy SL	5	55.5%
2. Xperia Zr	6	66.7%
3. Lumia 520	9	100%
4. One X	3	33.3%
5. Galaxy S3	1	11.1%
6. Lumia 710	6	66.7%
7. GT C322	1	11.1%
8. Iphone 4s	3	33.3%
9. Galaxy S Duos	3	33.3%
10. BB 9220	2	22.2%
11. Micromax A110	1	11.1%
12. Galaxy GT-1908	0	0.0%
13. LG-G2	3	33.3%

Table VI. Probable percentage match for known image.

Table VI gives us the information about the percentage match of the image with the various phones. We can see data bout the image is known thus we have an exact match.

Phones	Percentage
1.Lumia 520	100%
2.Xperia Zr	66.7%
3.Lumia 710	66.7%

Table VII Most Probable Solution for Picture-I

Tested Feature	Tested Feature Value	Probable (Nearest) Phones
1.Megapixel	3.1 mp	Lumia 520,Galaxy SL,Lumia 710, Galaxy S Duos
2.File Size	1090 Kb	Galaxy SL,Xperia Zr,Lumia 520, One X, Galaxy S3, I phone 4s, Galaxy S Duos, G2
3.Aperture	2.6	Galaxy SL,Galaxy S3,Lumia 710,C322,Iphone 4s,Galaxy S Duos,BB 9220,Galaxy GT-1908, G2
4.Focal Length	3.8mm	Galaxy S3,Galaxy GT-1908
5. Resolution	2048*1536	Lumia 520,Galaxy SL,Lumia 710, Galaxy S Duos
6.F. Number	2.6	Galaxy SL, Galaxy S3, Galaxy S Duos, G2
7. Dpi	96	Galaxy S3,C322, Galaxy S Duos, Galaxy GT-1908, G2
8. Attribute	A	Galaxy S3, Lumia 710,Iphone 4s, Galaxy S Duos,BB 9220,A110,Galaxy GT-1908
9. Exposure	1/8	G2

Table VIII. Probable Phones for the image about which information is not known

Phones	Number of Occurrences	Percentage
1. Galaxy SL	3	33.3%
2. Xperia Zr	1	11.1%
3. Lumia 520	2	22.2%
4. One X	1	11.1%
5. Galaxy S3	6	66.7%
6. Lumia 710	3	33.3%
7. GT C322	2	22.2%
8. Iphone 4s	3	33.3%
9. Galaxy S Duos	7	77.7%
10. BB 9220	2	22.2%
11. Micromax A110	1	11.1%
12. Galaxy GT-1908	4	44.4%
13. G2	5	55.5%

Table IX. Probable Percentage match for unknown image

In reality, the unknown image has been clicked from phone named Samsung Galaxy Fit which is not a part of our database.

7..CONCLUSION

In this paper, we examine the Exif information left on the images for identifying the source camera of a digital image and also implemented machine learning using k-NN algorithm. Classification based on the proposed features is built and trained to classify the images and also used to evaluate the effectiveness of these features which were taken into consideration for the classification. We show that it is feasible to classify images originating from a 13 different mobile phone camera models by Exif information and k-NN algorithm. Results are very promising for this technique we deployed but stand good against limited number of mobile phone cameras. Also, still work has to be done on the feature where identification is possible between two or more mobile phones of same model and company then the efficiency will increase.

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Although our initial results are encouraging, there are two main limitations. Firstly, it is possible that when the number of camera increases, it may not be able to distinguish the cameras by only using Exif data and k-NN algorithm. Secondly this method cannot classify between the images taken from two mobile phones of the same company and same model. However we believe our proposed features are evidence which can used together with the Kharrazi's proposed features [6] and our lens distortion parameters, for solving source camera identification problems

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