Source Camera Identification in Online Social Network

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ABSTRACT: *The online social network is becoming more and more advance now a day. Most of the online users are intent to share their information, especially photo through OSN application. Currently, there is a lot of research on Digital Image that focusing on source identification and forgery detection. This paper is focusing on analyzing the source camera identification in Online Social Network. The techniques consist of sensor imperfection that carries an abundance of information. It is reliable for identification purposes since the digital camera has its own uniquely sensor. Our proposed framework consists of techniques used for extracting the sensor noise from the digital images and then the feature extraction method is applied to extract the image feature. In this framework, Gaussian filter is used to obtain the noisy images. This noisy image is then used for the feature extraction of several texture features. Based on this idea, the extracted features taken from images are then applied to a classifier for identifying source camera. All datasets are analyzed Multilayer Perceptron. The experimental result shows that the best performance of the identification process by combining 4 texture features was achieved with an average accuracy 80%.*

Keywords: Texture Feature, Source Camera Identification, Feature Extraction, Digital Image Forensic, Online Social Network

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1. Introduction

In this day and age, there are over 950 million Facebook users around the world. Every 60 seconds about 136,000 of the photos has been uploaded. The effect of this current trend is the increasing number of crimes involving the online social user (e.g: online scamming, online threatening and etc). In Digital Image Forensics, it helps the investigator to identify the existence of digital photographic evidence. The main issues that facing by Digital Image Forensics are the source camera identification. There are a lot of techniques have been proposed in the literature. All the techniques generally working on the sensor noise which is left by a digital sensor while taking a picture. It acts as a fingerprint to the each of the digital cameras. These papers are focusing on extracting the source camera device from the online social digital image using sensor noise[1] and texture features. The remainder of the paper is organized as follows: Section 2 introduces the related works involve in source camera identification and texture feature. Section 3 describes the proposed framework for this research. Section 4 addresses the result and discussion. Lastly, in Section 5 will conclude the paper.

2. Related Work

Source Camera Identification is a technique to identify the particular digital camera device used for generating the digital image that very important for digital forensics. A survey of the different techniques and methods has been done and a new system has been proposed [3]. Sensor Pattern Noise is related to sensor imperfection based technique for Source Camera Identification which uses sensor noise for each device and stores the features that can be used for classification and identification. Every digital camera source has its own intrinsic features related to the device. These features are used as a unique identification mark to identify the image as its category or source.

The techniques in Geradts et. al [2] studies the CCD pixel defect that consists of appoint defects, hot point, dead pixel, pixel traps and cluster defects. The result shows that each of the cameras has its own different patterns.

Luka et. al [1] proposed an effective method on the Pixel Non-Uniformity (PNU) a kind of CCD noise that caused by pixel non-uniformities [3]. It's a great source for the retrieval the noise pattern and allows in identifying the sensor of the digital camera.

In Costa et. al [4] paper, suggest an approach for source camera identification by considering an Open Set scenario. It comprises with three strands definition of regions interest, features characterization and source camera attribution. Each region in the digital image contains different information of the digital source camera. Each of digital images has 9 regions of interest (ROI). Figure 1 illustrates the ROI in digital image. The region of interest is assumed with the principal axis of the lens and has more scene details. This is because the amateur photographer usually focusing at the center of the lens. Besides region 6 and 9 provide and important information because of some of the digital camera have an effect generated by the vignetting (also known as *'light fall-off'*). In their experiment, the result has achieved 94% to 98% accuracy of source camera identification.

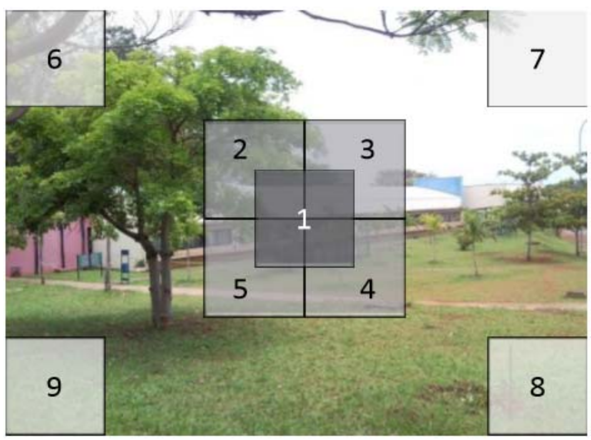

Figure 1. Region of Interest for digital image [5]

Meanwhile, paper from S. Bayram et al. [6] has proposed a technique based on sensor pattern noise which was a continuance over source camera identification techniques. It was a scheme which enabled demand of the technique in a more practical forensic scenario that was perceived by integrating digital cameras "Demosaicing characteristics" into the determination process which increased the authenticity of determination. Basically, in the camera identification approach in [6], the source camera of a query image was determined according to the correlation between the PRNU noises of a tested camera and the noise of the query image. The distribution of correlations of images was taken by different cameras of various manufacturers and was experimentally estimated, a threshold was determined from the distribution; a specified false acceptance rate (FAR) was achieved. Various methods have been applied for extracting this SPN and using it for device identification. The most common method is the use of Gaussian filters. The SPN extraction method gives the best possible results for source identification. The overall analysis of the methods studied above shows that SCI depends on the type of method applied and system designed for the extraction of noise. The other methods like metadata [7-10] , CFA [6, 11], image features [12-14] also yield good results.

3. Proposed Framework

The proposed framework consists of several steps of experiments. Each of the steps performs a specific task. Figure 2 below show the summarized process of the proposed framework. Moreover, the algorithms are implemented in MATLAB R2014b and performed on a standard laptop (Intel (R) Core (TM) i7 2.40GHz with 8.00GB RAM). There were 4 types of mobile phone used in this experiment (as shown in Table 1). Each of the mobile phones was used 50 images. It includes 3 main procedures denoising image, extraction process, and classification process. Several images have been uploaded and downloaded from OSN website; Facebook. The downloaded images are been used for the denoising process. The details of the process will be explained in details in the next section of this paper.

Meanwhile, in Table 1 is a list of mobile cameras used for this experiment. It consists of 4 types of iPhone model which each of the models used for 50 digital images with respective image size.

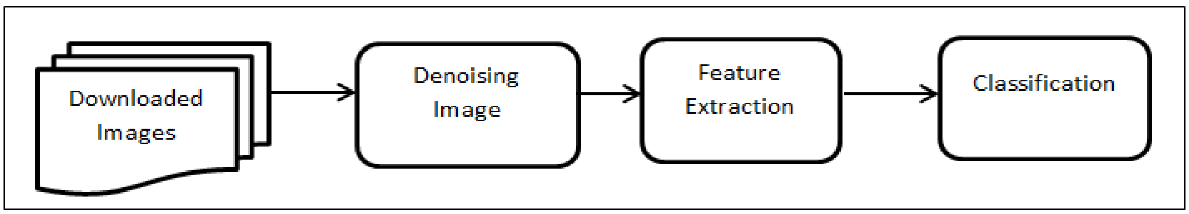

Figure 2. Proposed Framework

ID	Model	Image Size	No. of Images
I4	IPhone 4	717x960	50
I4S	IPhone 4S	720x960	50
I5	IPhone 5	720x960	50
I5S	IPhone 5S	720x960	50

Table 1. Mobile Phone used in the Experiment

3.1 Image Acquisition and Preprocessing

During the processing stage, denoising process was proposed by Lukas, Fridrich [1] were applied. After this process, image result from denoising (with a format of .png) will be used for the extraction process. Figure 3 shows the result from the denoising process.

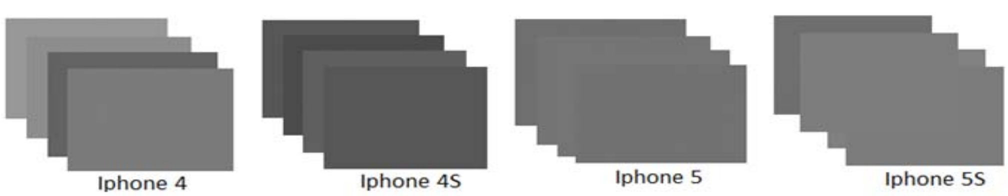

Figure 3. Noise residual image from different mobile phone

3.2 Feature Extraction

There is always a desire to include more features during the extraction process in hopes that it will improve the performance. Hence, in this experiment the feature was extracted from the images depending on their texture after denoising it.

The digital image is a set of pixels, that can define the texture as an entity that consisting a group of pixels. Texture analysis consists of 4 groups categories: model-based that based on the mathematical model, statistical-base is described the image by using the pure numerical pixel intensity value. In structural-based is need to understand the hierarchical structure of the digital image. Meanwhile, for the transform-based method it performing the modification to the digital image, and then will analyze as a representative proxy for the original image [15].

This paper will focus on the statistical-based method which depends on the relationship between the gray level of the digital images. .The Noise residual image is provided to the feature extraction using Gabor Feature, Gray Level Co-Occurrence Matrix (GLCM), Gray Level Run-Length Matrix (GLRLM) feature and Segmentation-based Fractal Texture Analysis (SFTA). Each of the texture features was be tested with the downloaded images and the result is an average of 70%. This 4 texture features combination has improved the performance of source identification result in average 80%. Details of the experiment and result are discussed in next section.

a) Gabor Feature

It is defined as a sinusoidal wave which known as a plane wave for 2D Gabor filter that multiplied by a Gaussian function [16]. The multiplication-convolution property (Convolution theorem), made the Fourier transform of a Gabor filter's response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed of a complex number or used individually.

b) Gray Level Co-Occurrence Matrix (GLCM)

A gray level co-occurrence matrix (GLCM) is a matrix that can be defined an image to be the distribution of co-occurring values at a given offset. A GLCM is a matrix is the number of rows and columns equal to the number of gray levels, G, in the image In Haralick et.al [17], the use of co-occurrence matrix or gray level co-occurrence matrix is a relationship between two neighboring pixels, the first pixel is known as a reference and the second is known as a neighbor pixel. Figure 4 is a list of GLCM properties used in this experiment.

c) Gray Level Run-Length Matrix (GLRLM

Gray-level run-length matrix (GLRLM) is a matrix where the texture features can be extracted for texture analysis. It can be understood as a pattern of gray intensity pixel in a certain direction from the reference pixels. Meanwhile, run length is the number of adjacent pixels that have the same gray intensity in a particular direction. The list of GLRM properties is in Figure 5.

4. Experimental Discussion

In order to evaluate the performance of the proposed framework, two experiments were conducted. It is to test the performance of the selected feature. The digital image is taken from our own database which consists of 200 digital images obtain from 4 models of mobile phone (as in Table 1). In this experiment, 50 images from each of the mobile phone were be uploaded in the OSN web (Facebook) and later will be downloaded and used for the experiment. Next, the downloaded images will go through the process of denoising and extraction process. Then the extraction result will be implemented in a dataset for analyzation process.

4.1 Experiment 1

In the first experiment, the performance for each of 4 texture feature was tested. A group of 4 mobile devices was tested. The process of the extraction is shown as the previous discussion in the above. The result of the accuracy for each feature as shown in Figure 6.

4.2 Experiment 2

The second experiment was organized by combining all the texture features. The result has shown the increasing to 80 % from the rest of the experiment result.

Moment	Equation
Energy	$f_1 = \sum_i \sum_j p(i, j)^2.$
Contrast	$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i, j) \middle\| \|i - j\| = n \right\}.$
Correlation	$f_3 \frac{\sum_i \sum_j (ij) p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y}.$
Homogeneity	$f_4 = \sum_i \sum_j \frac{1}{1 + (i - j)^2} p(i, j).$
Entropy	$f_5 = -\sum_i \sum_j p(i, j) \log(p(i, j)).$
Autocorrelation	$f_6 = \sum_i \sum_j (ij) p(i, j).$
Dissimilarity	$f_7 = \sum_i \sum_j \|i - j\| \cdot p(i, j).$
Cluster Shade	$f_8 = \sum_i \sum_j (i + j - \mu_x - \mu_y)^3 p(i, j).$
Cluster Prominence	$f_9 = \sum_i \sum_j (i + j - \mu_x - \mu_y)^4 p(i, j).$
Maximum Probability	$f_{10} = \underset{i, j}{\mathrm{MAX}}\, p(i, j).$

Figure 4. Feature set for GLCM

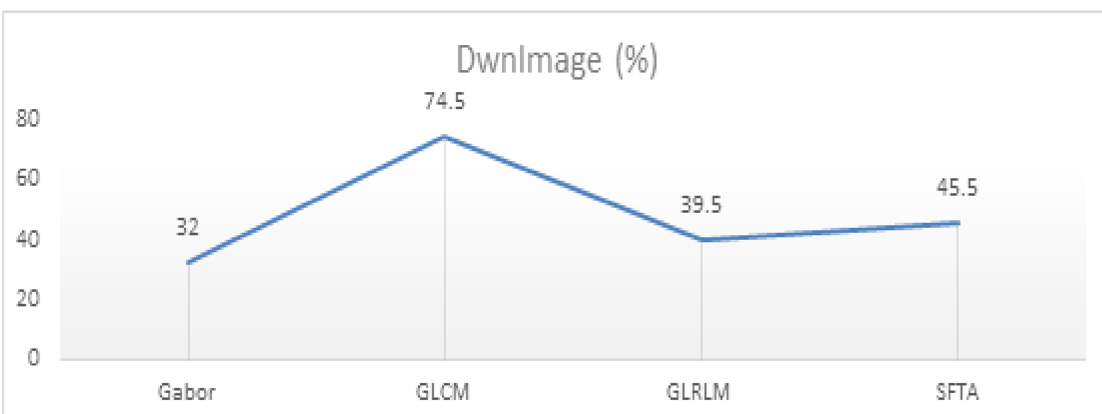

Figure 5. Feature set for GLRLM

Moment	Equation
Short Run Emphasis (SRE)	$\frac{1}{n}\sum_{i,j} \frac{p(i,j)}{j^2}$
Long Run Emphasis (LRE)	$\frac{1}{n}\sum_{i,j} j^2 p(i,j)$
Grey Level Non-Uniformity (GLN)	$\frac{1}{n}\sum_{i}\left(\sum_{j} p(i,j)\right)^2$
Run Length Non-Uniformity (RLN)	$\frac{1}{n}\sum_{i}\left(\sum_{i} p(i,j)\right)^2$
Run Percentage (RP)	$\sum_{i,j} \frac{n}{p(i,j)\, j}$
Low Grey Level Run Emphasis (LGRE)	$\frac{1}{n}\sum_{i,j} \frac{p(i,j)}{i^2}$
High Grey Level Run Emphasis (HGRE)	$\frac{1}{n}\sum_{i,j} i^2 p(i,j)$

Figure 6. Average accuracy for each of the feature

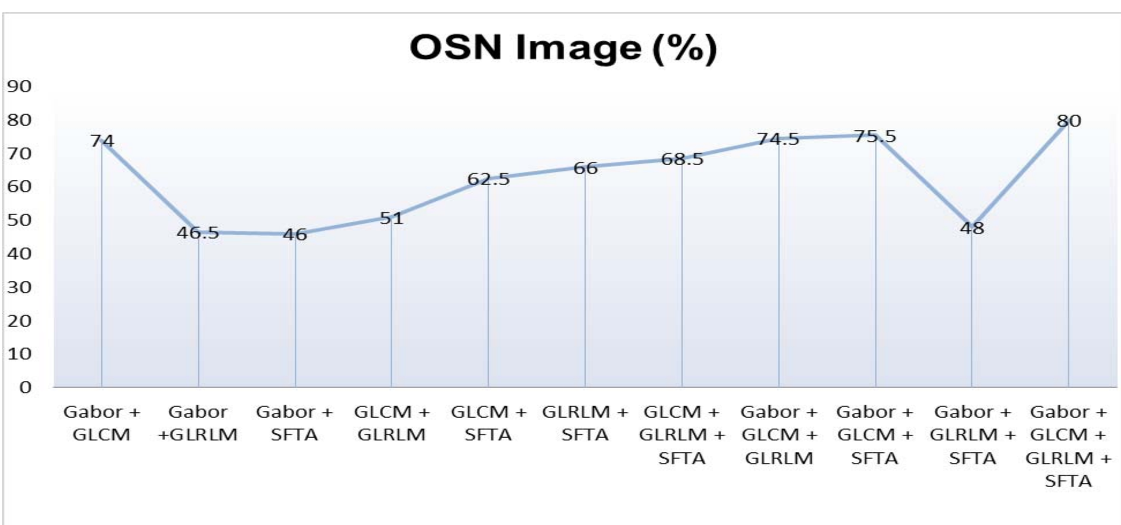

Figure 7. Average accuracy for combined feature

5. Results

This experiment was aimed to improve the accuracy of the single feature. Earlier experiment the result has shown that GLCM was the highest accuracy among the others feature. Since the feature set of GLCM is more than another feature set. Meanwhile, in the second experiment combination of Gabor + GLCM, Gabor +GLCM +GLRLM, and Gabor +GLCM + SFTA give an average result of 70% and above. It shows that combination of GLCM with the others features gave the better accuracy compare that the combination without GLCM features.

6. Conclusion

There is a potential where texture analysis is used for source camera identification in Online Social Network images. In this research, feature extraction for source camera identification is proposed. The experiment result has shown that there is a possibility this texture feature can be used for source camera identification. The variation combination of Gabor, GLRM and SFTA give an average result of 50 % for OSNs images. Meanwhile, the combination of Gabor, GLCM, GLRM, and SFTA feature performed well in identifying the source camera for OSNs which averagely is 80% accurate. By using a proper combination texture feature and selection method, the performance of accuracy may be improved for the future work.

Acknowledgment

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression, "One of us (R. B. G.) thanks . . ." Instead, try "R. B. G. thanks". Put applicable sponsor acknowledgments here; DO NOT place them on the first page of your paper or as a footnote.

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