Source Camera Identification in Forensic View of Images

A Project Submitted

In Partial Fulfilments of the Requirements

For the Degree of Bachelor of

Technology

In

COMPUTER SCIENCE AND ENGINEERING

(2017-2021)

Submitted By:
Popita Gorai (35000117048)
Saktipada Das (35000117035)

Guided By:
Asst. Prof Pabitra Roy
Department of Computer
Science And Engineering

UNDERTAKING

I declare that the work presented in this project titled "Source Camera Identification in Forensic View of Images", submitted to the Department of Computer Science and Engineering at Ramkrishna Mahato Government Engineering College, for the award of the Bachelor of Technology Degree in Computer Science and Engineering (2017-2021), is our original work. We have not plagiarized or submitted the same work for the award of any other degree. In case this undertaking is found incorrect, We accept that our degree may be unconditionally withdrawn.

July 2021
Place: Purulia

Students names:
Popita Gorai
Saktipada Das

CERTIFICATE

This certified that the work contained in the project titled "Source Camera Identification in forensic View of Images", by Popita Gorai (35000117048) and Saktipada Das (35000117035) of Department of Computer Science and Engineering in final year in academic session 2020- 2021, has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

Asst. Prof. Pabitra Roy,
Dept. of C.S.E
Ramkrishna Mahato Government
Engineering College

Dr. Prasun Halder,
H.O.D of C.S.E Dept.
Ramkrishna Mahato Government
Engineering College

Acknowledgements

We take this occasion to thank God, almighty for blessing us with his grace and taking our endeavor to a successful culmination. I extend my sincere and heartfelt thanks to our esteemed guide, **Prof. Pabitra Roy**, for providing us with the right guidance and advice at the crucial junctures and for showing me the right way. I extend my sincere thanks to our respected *Head of the department* **Dr. Prasun Halder**, for allowing us to use the facilities available. I would like to thank the other faculty members also, at this occasion. Last but not the least, I would like to thank my friends and family for the support and encouragement they have given me during the course of our work.

-Popita Gorai
-Saktipada Das

Abstract:

The manipulation of digital images has become very common in recent years. Thus, it is possible to cut, clone, and resize an image very quickly, which makes it challenging to validate the integrity and authenticity of images. Furthermore, digital images can be used by forensic experts in their forensic investigations. In this context, digital image forensics (DIF) has emerged as an essential area of expertise focused on verifying the authenticity and integrity of digital images.

Digital image processing is continuously an exciting field as it gives improved pictorial information for human clarification and processing of image data for storage, transmission, and representation for machine view. Image Processing is a technique to increase raw images expected from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal everyday life for several applications. This paper presents Image processing Source Camera Identification. In this domain basically start playing with images in order to understand them. So here we use many many techniques which includes feature extraction as well and algorithms to detect features such as shaped edges in a digital image to process them to achieve the best solution.

Keywords- Digital Image Processing,feature extraction, Image classification, Image Compression, Mean, Median and Standard deviation are proposed for efficient retrieval .

INTRODUCTION:

First What Exactly Is a Digital Image?

Whether you take a picture with a digital camera or use a scanner to bring a photo (or other artwork) into your memory. You are digitizing the image. That is, digits not as in a finger or toe, but as in a number. Computers do everything, absolutely everything, by processing numbers, and the basic language of computers is binary code. Whether it's a photo of a Nature , a client's name in a database.

Likewise, a single pixel in a digital image is simply a square of color. It doesn't become a meaningful part of your digital image until it's surrounded by other pixels of the same or different color, creating a unified whole of a meaningful *picture. How you manipulate those pixels, from the time you capture the image digitally until you output the image to paper or the web, determines how successfully your pixels will represent your image.*

Currently, digital cameras have become very popular, and it is possible to find them in a variety of devices including smartphones, monitoring and surveillance cameras, etc. In addition, powerful image editing software has become very common. Due to such abundant availability of digital images, they can be used by forensic experts, for example, to help solve crimes. However, performing manual analysis of a large volume of digital images is a tedious task. So we will perform optimal solutions of digital image processing in a systematic way.

Image manipulation occurs when operations are performed on the image in order to modify it. Image forgery considers that the entire image is manipulated with malicious intent, while in the image tampering, only parts of the image are intentionally modified. Image generating is a particular type of image creating technique, using computer software or algorithms to produce an image simulating real-world scenes. In steganography, the image is modified such that it can store secret information invisible to the human eye. Image watermarking considers the alteration of the image to insert a mark that can guarantee its authenticity.
As we live in an era of high technology, digital images are commonly used due to the availability of various models of digital cameras. Each day, more and more digital cameras are invented by technology companies. Consequently, digital cameras have become more affordable for the consumers to own. Mobile phones are now equipped with digital cameras. This has further increased the number of individuals owning image capturing devices. As a consequence, thousands of images are being created each day with some of them capturing a critical moment in time such as a crime. These images can be used in court as evidence to demonstrate the relationship between the suspects and criminals. However, a major issue in using digital images as evidence in court is that digital images are easily created and manipulated without leaving any obvious traces of modifications. Evidence manipulation causes the credibility and authenticity of the digital image to be questioned.

Therefore, we need more tools and applications to address the problem of verifying the authenticity of an image. Image authenticity is able to be verified through various methods ranging from a simpler method like comparing the EXIF metadata method to a complex method like tracing the digital fingerprints of the image. The latter seems to be more reliable and has attracted a growing interest among researchers in image forensics. The digital fingerprints of an image provide distinguishing characteristics of the image. Therefore, the forensic analyzer is able to track the possible source camera of the image under investigation whether it is acquired by the device that it is claimed to be sensed with. Source camera identification has been the focus of recent research with various techniques being investigated.

The image processing deals with image acquisition, Image enhancement, image segmentation, feature extraction, image classification, a regular study on the importance of image processing and its applications to the field of computer revelation is conceded out in this paper. In an image processing operation, the input given is an image and its output is an enriched high-quality image as per the methods used.

The method of image processing is used to do some processes on a picture like an image enhancement or to remove some functional data from the image. Image processing is one kind of signal processing, where the input is a picture, as well as the output, are features or characteristics allied with the image.

Problem Description

In image retrieval system for searching, browsing, and retrieving images from a large database of images. Most conventional and common methods of image retrieval utilize some method of adding metadata such as tokens, captioning , keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Some systems are working with lower level features, Manual image annotation is time-consuming, laborious and expensive. To address this, many researchers are proposed on automatic user-friendly image retrievals using different methods.

Content-based means that the search will analyze the actual contents of the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. Without the ability to examine image content, searches must rely on metadata such as captions or keywords, which may be laborious or expensive to produce. In this paper proposed methods are providing the best solution in a large image set.

In this paper we have discussed about an image belongs to which source camera model. Not only camera models about the features properties and the color distributions and trend multiple images by using appropriate algorithms. And then we can easily find the correct source camera model.

Previous Work

We all know how images are important in our daily life. The features of data, especially images is one of the crucial aspects in the gigantic and still expanding domain of the digital world.. Various techniques have been proposed in literature till date, each having an edge over the other, to catch up to the ever growing need to optimize features extraction Techniques We study many of these techniques and use best Techniques .

The concept of feature mining, in which our goal is to minimize the human effort needed to explore and organize the vast space of possible features for image classification.

Features Extractions Techniques:

A. Color Features:

A color image is a combination of some basic colors. In MATLAB breaks each individual pixel of a color image (termed 'true color') down into Red, Green and Blue values.[2] We are going to get as a result, for the entire image is 3 matrices, each one representing color features. The three matrices are arranging in sequential order, next to each other creating a 3 dimensional m by n by 3 matrices. An image which has a height of 5 pixels and width of 10 pixels the resulting in MATLAB would be a 5 by 10 by 3 matrices for a true color image.

B. Texture Features:

Using RGB images allows the color to vary within a single character, though the color values need to be assigned to the image data before transfer to the pipeline. A common limitation with both bitmap and pixel image character text rendering is that the text cannot be easily scaled or rotated. Limited scaling can be achieved using pixel zoom operations, but no filtering is performed on the images so the results deteriorate very quickly.

C. Content-Based Image Retrieval (CBIR):

CBIR is according to the user-supplied in the bottom characteristics, directly find out images containing specific content from the image library The basic process: First of all, do appropriate pre-processing of images like size and image transformation and noise reduction is taking place, and then extract image characteristics needed from the image according to the contents of images to keep in the database. When we retrieve to identify the image , extract the corresponding features from a known image and then retrieve the image database to identify the images which are similar with it, also we can give some of the characteristics based on a query requirement, then retrieve out the required images based on the given suitable values. In the whole retrieval process, feature extraction is essential.[2] it is closely related to all aspects of the feature, such as color, shape, texture and space.

Most present-day NR IQA algorithms assume that the distorting medium is known—for example, compression, loss induced due to noisy channel, etc. Based on this assumption, distortions specific to the medium are modeled and quality is assessed. By far the most popular distorting medium is compression, which implies that blockiness and blurriness should be evaluated. In the following, we study blind QA algorithms that target three common distortion categories: JPEG compression, JPEG2000 compression, and blur. [6]

So far we know there is a popular distortion medium compression, which implies that blockiness and blurriness should be evaluated. we study blind QA algorithms that
target three common distortion categories: JPEG compression,
JPEG2000 compression, and blur.

general approach to NR JPEG IQA is to measure edge strength at block boundaries and relate this
strength and possibly some measure of image activity to perceived quality.This algorithm works either using a training set, or by combining features in an intelligent fashion.

JPEG2000 IQA, generally works on the image which are modeled by measuring edge-spread using an edge-detection-based approach and this edge spread is related to quality.

Sharpness/Blur IQA , Blur IQA algorithms model edgespreads and relate these spreads to perceived quality, similar to the approach followed by NR JPEG2000 IQA algorithms. Edge strengths are quantified using a variety of techniques, including block kurtosis of DCT coefficients, iterative thresholding of a gradient image , and measuring the probability of blur detection or model the just-noticeable-blur in an image.

Holistic IQA Algorithms: this method proposed to characterize image quality based on three quantities—edge sharpness, random noise level (impulse/additive white Gaussian noise),
and structural noise. Edge sharpness is measured using an edge-detection approach, while the random noise level is measured using a local smoothness approach (impulse noise) and PDE-based model (Gaussian noise).

Image Quality Attributes

- **Sharpness** determines the amount of detail an image can convey. System sharpness is affected by the lens (design and manufacturing quality, focal length, aperture, and distance from the image centre) and sensor (pixel count and anti-aliasing filter). In the field, sharpness is affected by camera shake (a good tripod can be helpful), focus accuracy, and atmospheric disturbances (thermal effects and aerosols). Lost sharpness can be restored by sharpening, but sharpening has limits. Oversharpening, can degrade image quality by causing "halos" to appear near contrast boundaries. Images from many compact digital cameras are sometimes oversharpened to compensate for lower image quality.[7]
- **Noise** is a random variation of image density, visible as grain in film and pixel level variations in digital images. It arises from the effects of basic physics— the photon nature of light and the thermal energy of heat— inside image sensors. Typical noise reduction (NR) software reduces the visibility of noise by smoothing the image, excluding areas near contrast boundaries. This technique works well, but it can obscure fine, low contrast detail.

- **Dynamic range** (or exposure range) is the range of light levels a camera can capture, usually measured in f-stops, EV (exposure value), or zones (all factors of two in exposure). It is closely related to noise: high noise implies low dynamic range.
- **Tone reproduction** is the relationship between scene luminance and the reproduced image brightness.
- **Contrast**, also known as gamma, is the slope of the tone reproduction curve in a log-log space. High contrast usually involves loss of dynamic range — loss of detail, or clipping, in highlights or shadows.
- **Color accuracy** is an important but ambiguous image quality factor. Many viewers prefer enhanced color saturation; the most accurate color isn't necessarily the most pleasing. Nevertheless, it is important to measure a camera's color response: its color shifts, saturation, and the effectiveness of its white balance algorithms.
- **Distortion** is an aberration that causes straight lines to curve. It can be troublesome for architectural photography and metrology (photographic applications involving measurement). Distortion tends to be noticeable in low cost cameras, including cell phones, and low cost DSLR lenses. It is usually very easy to see in wide angle photos. It can be now be corrected in software.
- **Vignetting**, or light falloff, darkens images near the corners. It can be significant with wide angle lenses.
- **Exposure accuracy** can be an issue with fully automatic cameras and with video cameras where there is little or no opportunity for post-exposure tonal adjustment. Some even have exposure memory: exposure may change after very bright or dark objects appear in a scene.
- **Lateral chromatic aberration** (LCA), also called "color fringing", including purple fringing, is a lens aberration that causes colors to focus at different distances from the image center. It is most visible near corners of images. LCA is worst with asymmetrical lenses, including ultrawides, true telephotos and zooms. It is strongly affected by demosaicing.[7]
- **Lens flare**, including "veiling glare" is stray light in lenses and optical systems caused by reflections between lens elements and the inside barrel of the lens. It can cause image fogging (loss of shadow detail and color) as well as "ghost" images that can occur in the presence of bright light sources in or near the field of view.

- **Color moiré** is artificial color banding that can appear in images with repetitive patterns of high spatial frequencies, like fabrics or picket fences. It is affected by lens sharpness, the anti-aliasing (lowpass) filter (which softens the image), and demosaicing software. It tends to be worst with the sharpest lenses.
- **Artifacts** – software (especially operations performed during RAW conversion) can cause significant visual artifacts, including data compression and transmission losses (e.g. Low quality JPEG), oversharpening "halos" and loss of fine, low-contrast detail.[7]

DIIVINE is a distortion-agnostic approach to blind IQA that utilizes concepts from natural scene statistics (NSS) to not only quantify the distortion and hence the quality of the image, but also qualify the distortion type afflicting the image. The Distortion Identification-based Image Verity and INtegrity Evaluation (DIIVINE) index utilizes a 2-stage framework for blind IQA that first identifies the distortion afflicting the image and then performs distortion-specific quality assessment.

Our computational theory for distortion-agnostic blind IQA is based on the regularity of natural scene statistics (NSS); for example, it is known that the power spectrum of natural scenes fall-off as (approximately) 1/f^b , where f is frequency. NSS models for natural images seek to capture and describe the statistical relationships that are common across natural (undistorted) images. Our hypothesis is that, the presence of distortion in natural images alters the natural statistical properties thereby rendering the image 'un-natural'. NR IQA can then be accomplished by quantify- ing this 'un-naturalness' and relating it to perceived quality.
The Distortion Identification-based Image Verity and INtegrity Evaluation (DIIVINE) – divines the quality of an image without any need for a reference or the benefit of distortion models, with such precision that its performance is statistically indistinguishable from popular FR algorithms such as the structural similarity index (SSIM). The DIIVINE approach is distortion-agnostic, since it does not compute distortion-specific indicators of quality, but utilizes an NSS-based approach to qualify as well as quantify the distortion afflicting the image. The approach is modular, in that it can easily be extended beyond the pool of distortions considered here.
DIIVINE is based on natural scene statistics which govern the behavior of natural images.DIVINE, the statistical features extracted and their relevance to perception and thoroughly evaluate the algorithm on the popular LIVE IQA

database. Further, we compare the performance of DIIVINE against leading full-reference (FR) IQA algorithms and demonstrate that DIIVINE is statistically superior to the often used measure of peak signal-to-noise ratio (PSNR) and statistically equivalent to the popular structural similarity index (SSI).

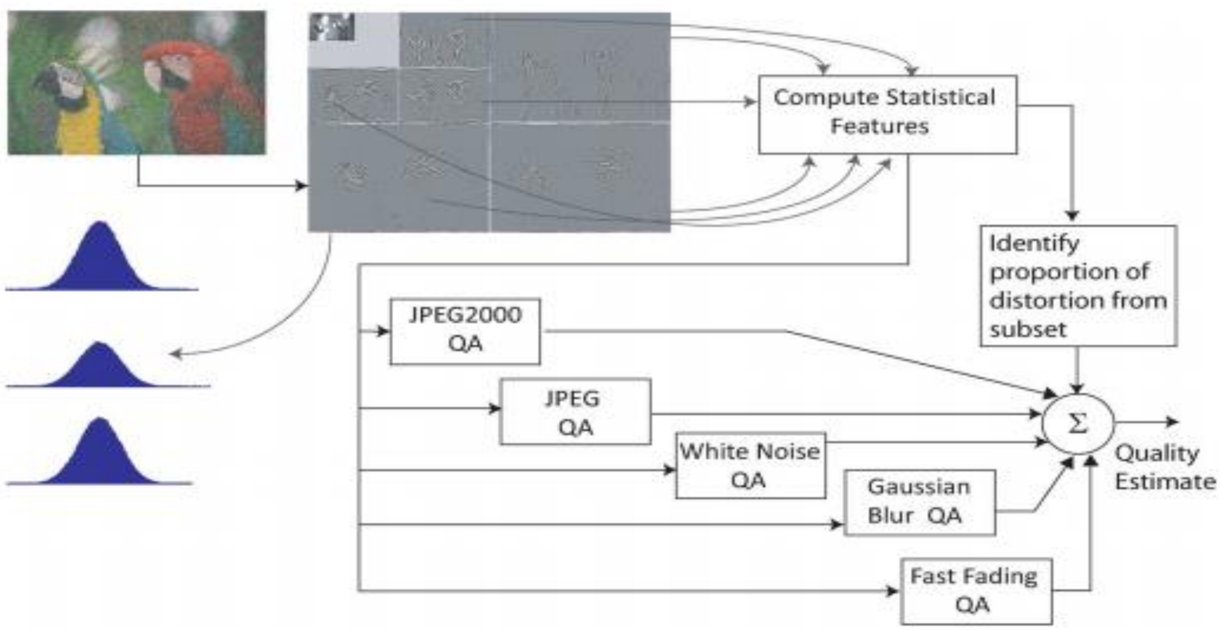

Fig. 1. Proposed Distortion identification-based Image Verity and INtegrity Evaluation (DIIVINE) index consists of two stages: probabilistic distortion identification followed by distortion-specific quality assessment as illustrated here.

Proposed Method

- Proposed system uses a large set of Images from the Database.
- Used Histogram Equalization which helps in enhancing of contrast image.
- Proposed system selected approx. 1000 of images from different Camera Models and extracted all images features values for problem solving.
- Proposed system created .xlsx files with features matrixes 1X88 per image.
- Proposed system again created a Training set of 80% images features and 20% of Testing Set of images features.

Feature Extraction

Feature detection selects regions of an image that have unique content, such as corners or blobs. Use feature detection to find points of interest that you can use for further processing. These points do not necessarily correspond to physical structures, such as the corners of a table. The key to feature detection is to find features that remain locally invariant so that you can detect them even in the presence of rotation or scale change.

Feature extraction involves computing a descriptor, which is typically done on regions centered around detected features. Descriptors rely on image processing to transform a local pixel neighborhood into a compact vector representation. This new representation permits comparison between neighborhoods regardless of changes in scale or orientation. Descriptors, such as SIFT or SURF, rely on local gradient computations. Binary descriptors, such as BRISK, ORB or FREAK, rely on pairs of local intensity differences, which are then encoded into a binary vector.

Implementation of Features Extraction:

Many data analysis software packages provide for feature extraction and dimension reduction. Common numerical programming environments such as MATLAB, SciLab, NumPy, Sklearn and the R language provide some of the simpler feature extraction techniques (e.g. principal component analysis) via built-in commands. More specific algorithms are often available as publicly available scripts or third-party add-ons. There are also software packages targeting specific software machine learning applications that specialize in feature extraction.

Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task.

There are lots of image preprocessing techniques available here we used,

A histogram of an image is the graphical interpretation of the image's pixel intensity values. It can be interpreted as the data structure that stores the frequencies of all the pixel intensity levels in the image.

So, Historigram equalization is a process in which we enhance the contrast of an image by spreading out the most frequent intensity values or stretches out the intensity range of the image. By accomplishing this, histogram equalization allows the image's areas with lower contrast to gain a higher contrast.

Let Im be a given image represented as a m_c by m_r matrix of integer pixel intensities ranging
from 0 to L − 1. L is the number of possible intensity values, often 256. Let denote the H normalized histogram of Im with a bin for each possible intensity. So

$$H_n = \frac{\text{number of pixels with intensity n}}{\text{total number of pixels}} \quad , n = 0, 1... , L - 1.$$

The histogram equalized image $Hist_{eq}$ will be defined by

$$Hist_{eq(i,j)} = \text{floor}\left((L-1)\sum_{n=0}^{Im_{i,j}} H_n\right), \qquad \rightarrow(1)$$

Where floor () rounds down to the nearest integer. This is equivalent to transforming the
Pixel intensities, B, of Im by the function

$$T_{(B)} = \text{floor}\left((L-1)\sum_{n=0}^{B} H_n\right)$$

The motivation for this transformation comes from thinking of the intensities of Im and $hist_{eq}$ as
Continuous random variables X, Y on [0, L − 1] with Y defined by

$$Y = T(X) = (L-1)\int_0^X H_X(x)dx, \qquad \rightarrow(2)$$

Where H_x is the probability density function of Im. T is the cumulative distributive function
of X multiplied by (L − 1). Assume for simplicity that T is differentiable and invertible. It

can then be shown that Y defined by T(X) is uniformly distributed on [0, L − 1], namely
that H_Y (y) = $\frac{1}{L-1}$

$$\int_0^y H_Y(Z)dz \quad \text{=Probability that} \quad 0 \le Y \le y$$

$$= \quad \text{Probability that} \quad 0 \le X \le T^{-1}(y)$$

$$= \quad \int_0^{T^{-1}(y)} H_X(w)dw$$

$$\frac{d}{dy}\left(\int_0^y H_Y(z)dz\right) = H_Y(y) = H_X(T^{-1}(y))\frac{d}{dy}(T^{-1}(y)))$$

Note that $\quad \frac{d}{dy}T(T^{-1}(y))) = \frac{d}{dy}y = 1$, so

$$\frac{dT}{dy}\bigg|\, x = T^{-1}(y)\,\frac{d}{dy}(T^{-1}(y))) = (L-1)\, H_X(T^{-1}(y))\,\frac{d}{dy}(T^{-1}(y)) = 1$$

Which means $\quad H_Y(y) = \frac{1}{L-1}$

Our discrete histogram is an approximation of HX(x) and the transformation in Equation
1 approximates the one in Equation 2. While the discrete version won’t result in exactly
Flat histograms, it will flatten them and in doing so enhance the contrast in the image. The
result of applying Equation 1 to the ‘CROPED.JPG’ test image is shown in Figure 2 .

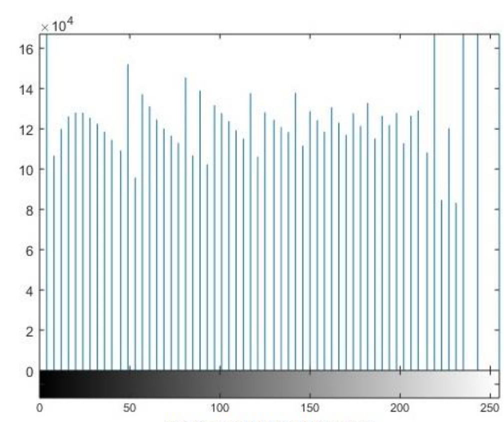

Figure 2

<u>Distortion Identification-based Image Verity and INtegrity Evaluation (DIIVINE)</u>

Given each distortion details in the (previous work section) affects sub band statistics characteristically,
The goal is to compute marginal and joint statistics
across sub bands in order to extract features that are relevant to
the perceived quality of the image.

1) *Scale and Orientation Selective Statistics ($f_1 - f_{24}$):* Sub band coefficients from each of the 12 sub bands are parameterized using a generalized Gaussian distribution (GGD). The GGD is

$$f_X(x, \mu, \sigma^2, \gamma) = a e^{-[b\, x-\mu|]^{-\gamma}} \qquad x \in \Re$$

Where μ, σ^2 , γ and are the mean, variance, and shape-parameter
of the distribution and

$$a = \frac{b\gamma}{2\Gamma(1/\gamma)}$$

$$b = \frac{1}{\sigma}\sqrt{\frac{\Gamma(3/\gamma)}{\Gamma(1/\gamma)}}$$

$\Gamma(.)$ is the gamma function:

$$\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt \qquad x > 0$$

The shape parameter γ controls the “shape” of the distribution. For example, $\gamma = 2$ yields a Gaussian distribution and $\gamma = 1$ yields a Laplacian distribution. The parameters of the distribution (μ , σ^2, and γ) are estimated using the method proposed in. GGD has also been used before to model the sub band Statistics of natural images in RR IQA Since wavelet Sub band responses are zero mean, we have to estimate σ^2 and for each sub band leading to a total of 24 features. $f_1 - f_{12}$ Correspond to σ^2 across sub bands and $f_{13} - f_{24}$ correspond to γ across sub bands.

2) Orientation Selective Statistics ($f_{25} - f_{31}$): Images are naturally multiscale. Further, there exists a relationship between subbands at the same orientation and across different scales. Distortions in an image will affect these across-scale statistics. We compute two parameters—σ^2 and γ .In our experiments, σ^2 does not add any information about the perceived quality, and hence, we use only the computed γ's as features. Further, we also compute a GGD fit when all of the

Subbands are stacked together and use the γ parameter again as our feature. Thus, $f_{25} - f_{30}$ correspond to γ from the statistics across scales over different orientations, while f_{31} corresponds to γ from the statistics across sub bands.

3) Correlations Across Scales ($f_{32} - f_{43}$): One of the

Primary stages in human visual processing is filtering of the visual stimulus by the retinal ganglion cells. These cells have center-surround-difference properties and have spatial responses that resemble difference of Gaussians (DoG) functions

. The responses of these cells serve a variety of likely purposes including dynamic range compression, coding, and enhancement of features such as edges. Image compression algorithms such as EZT and SPIHT offer evidence of correlations across scales as well. Statistics of edges have been used for blur quality assessment . it is reasonable to suppose that there exist elegant statistical properties between high-pass (HP) responses of natural images and their band-pass (BP) counterparts. Indeed, in our experiments, we found that such a relationship exists for natural images and this relationship is affected by the presence of distortion. We model high-pass

Band-pass correlations in order to capture these dependencies. Each BP sub band is compared with the HP residual band (obtained from the steerable pyramid transform) using a windowed structural correlation.

4) Spatial Correlation ($f_{44} - f_{73}$): Throughout this discussion, we have emphasized the observation that natural images are highly structured and that distortions modify this structure. While we have captured many such modifications in the sub band domain, one particular form of scene statistics that remains neglected is the spatial structure of the subbands. Natural images have a correlation structure that, in most places, smoothly varies as function of distance. In order to archive capture spatial correlation statistics we compute p(x,y) ,between two random variables x and . To estimate correlation between these two variables

5) Across Orientation Statistics ($f_{74} - f_{88}$): One set of statistics that remains unexplored are statistical correlations that natural images exhibit across orientations. In order to capture .the distortion-induced modifications to these statistical correlations across orientations, we compute windowed structural correlation (same as the across scale statistics) between all possible pairs of subbands at the coarsest scale. The set of features is the lowest 5% of the structural correlation values so obtained for each pair, leading to a total ${}^{n}_{2}c$ of features—($f_{74} - f_{88}$).

Table-1

Feature ID	Feature Description	Computation procedure
$f_1 - f_{12}$	Variance of subband coefficients	Fitting a generalized Gaussian to subband coefficients
$f_{13} - f_{24}$	Shape parameter of subband coefficients	Fitting a generalized Gaussian to subband coefficients
$f_{25} - f_{31}$	Shape parameter across subband coefficients	Fitting a generalized Gaussian to orientation subband coefficients
$f_{32} - f_{43}$	Correlations across scales	Computing windowed structural correlation between filter responses
$f_{44} - f_{73}$	Spatial correlation across subbands	Fitting a polynomial to the correlation function
$f_{74} - f_{88}$	Across orientation statistics	Computing windowed structural correlation between adjacent orientations at same scale

Tools used:

Support vector machines(SVM) are supervised learning models with associated learning algorithms that analyze Training data used for classification and Predict the testing models. Learning the parameters of a prediction function and testing.

cross validation :
This method, also known as Monte Carlo cross-validation, creates multiple random splits of the dataset into training and validation data. For each such split, the model is fit to the training data, and predictive accuracy is assessed using the validation data. The results are then averaged over the splits. Accuracy of the model depends on the variable parameter ,
-g gamma : set gamma in kernel function (default 1/num_features)
-c cost : set the parameter C of C-SVC, epsilon-SVR, and nu-SVR (default 1)
We have to set this value for our model by hit and trial.

In our project g=5.1
c=1000

Experiment Result And Discussion

EXPERIMENT CAMERA MODEL WITH NUMBER OF TRAINING IMAGES AND TESTING IMAGES

SL NO.	**CAMERA MODEL**	**Resolution (*.jpg)**	**TOTAL IMAGES**	**TRAINING IMAGES**	**TESTING IMAGES**
1.	A11_Xiaomi5	2048x2048	190	150	40
2.	A13_Huawei-RY6	2048x2048	190	150	40
3.	A14_Xiaomi-5A	2048x2048	190	150	40
4.	A15_Xiaom-3	2048x2048	190	150	40
5.	I01_iphone8	2048x2048	190	150	40
6.	I02_iphonese	2048x2048	189	150	39
7.	I03_iPhone7	2048x2048	195	150	45
8.	A16_OnePlus-3t	2048x2048	186	150	36
			1520	1200	320

Table 1

Procedure of our Work

1. As per Table 1 we have taken 8 camera models for our experiment.
2. For our experiment we manipulate the image sets of each camera model into 80% of image sets as “Training Model” and 20% as “Testing Model”
3. We are using An Algorithm where we crop each image into smaller size from the centre portion without losing our required features.
4. Then we apply Historigram Equalization for enhancement of images.
5. By using “Feature extraction descriptor” we extract features of each image of length 1X88 and create spreadsheets of Training model and Testing model.
6. Finally we trained our Model Through Support Vector Machine (SVM) ,and get Prediction Sets of Testing models.

Efficiency Table								
Model Identification					**Devices Identification**			
Sl. No	**Camera Model Name**	**No. Of Images**	**Correct Detection**	**Efficiency**	**Camera model Name**	**NO. of images**	**Correct Detection**	**Efficiency**
1	**A11_Xiaomi5**	40	40	100	**Xiaomi (3 Models)**	120	115	95.83333333
2	**A13_Huawei-RY6**	40	36	90	**Huawei (1 Models)**	40	36	90
3	**A14_Xiaomi-5A**	40	36	90	**Apple Iphone (3 Models)**	124	115	92.74193548
4	**A15_Xiaom-3**	40	39	97.5	**OnePlus(1 Model)**	36	34	94.44444444
5	**I01_iphone8**	40	40	100		**320**	**300**	**93.25492832**
6	**I02_iphonese**	39	33	84.61538462				
7	**I03_iPhone7**	45	42	93.33333333				
8	**A16_OnePlus-3t**	36	34	94.44444444				
		320	**300**	**93.7366453**				

Table 2

The Table 2 shows the outcomes of our experiments, and got Accuracy of 93.73% .

Conclusion

Finally, we conclude our work and present the results of project work. This is in the previous chapter. This is a simple but effective Model to identify the originality and Authenticity of the Source Camera of an Image. Our algorithm performs well under normal circumstances. Efforts will be made to optimize space and decrease susceptibility to error. This is a simple Model where we can easily find the Origin of Digital Images.The above discussed technique prefers the Historigram Equalization(HE) where we enhance the image quality and crop the image from center without losing required features.Thats features helps to find the problem statements of our project .Its is a very reliable and effective for Forensic View.

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