International Journal of Innovative Research in Electronics and Communications (IJIREC)
Volume 2, Issue 6, August 2015, PP 7-14
ISSN 2349-4042 (Print) & ISSN 2349-4050 (Online)
www.arcjournals.org

Machine-Learning Algorithm for Digital Image Forgeries by Illumination Color Classification

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Abstract: *In this method we propose the method to detect the forensic in the photography. For that here we use the svm classifier for the forensic detection. Initially we identify the illuminant map in the image. We find the face from the photography. For the face detect here we use the violo john method. After face detection After that we identify the GLCM (Gray Level Co-Occurance Matrix). In GLCM is the statistical information of the image such as energy, entropy, correlation sum of energy and sum of correlation are calculated. And also we extract the LBP feature. The extracted feature will pass to the SVM classifier for the training. SVM is stands for Support vector machine. It is a binary classifier. It is a kernel based learning classifier. The trained classifier will predict about the image whether it is original or forensic image.*

1. Introduction

In this work, we make an important step towards minimizing user interaction for an illuminant-based tampering decision-making. We propose a new semiautomatic method that is also significantly more reliable than earlier approaches. Quantitative evaluation shows that the proposed method achieves a detection rate of 86%, while existing illumination-based work is slightly better than guessing. We exploit the fact that local illuminant estimates are most discriminative when comparing objects of the same (or similar) material. Thus, we focus on the automated comparison of human skin, and more specifically faces, to classify the illumination on a pair of faces as either consistent or inconsistent. User interaction is limited to marking bounding boxes around the faces in an image under investigation. In the simplest case, this reduces to specifying two corners (upper left and lower right) of a bounding box. In summary, the main contributions of this work are: • Interpretation of the illumination distribution as object texture for feature computation. A novel edge-based characterization method for illuminant maps which explores edge attributes related to the illumination process. The creation of a benchmark dataset comprised of 100 skillfully created forgeries and 100 original photographs

2. Literature Survey

2.1. Estimation of Image Rotation Angle Using Interpolation-Related Spectral Signatures with Application to Blind Detection of Image Forgery:Weimin Wei, Shuozhong Wang, Xinpeng Zhang, and Zhenjun Tang

Here they develop an image rotation angle estimator based on the relations between the rotation angle and the frequencies at which peaks due to interpolation occur in the spectrum of the image's edge map. We then use rescaling/rotation detection and parameter estimation to detect fake objects inserted into images. When a forged image contains areas from different sources, or from another part of the same image, rescaling and/or rotation are often involved. In these geometric operations, interpolation is a necessary step. By dividing the image into blocks, detecting traces of rescaling and rotation in each block, and estimating the parameters, we can effectively reveal the forged areas in an image that have been rescaled and/or rotated. If multiple geometrical operations are involved, different processing sequences, i.e., repeated zooming, repeated rotation, rotation-zooming, or zooming-rotation, may be determined from different behaviors of the peaks due to rescaling and rotation. This may also provide a useful clue to image authentication.

2.1.1. Estimation of Rotation Angle: To develop an image rotation angle estimator, consider the interpolation involved in rotation. Assume that an image is rotated about its center. As pixels are located on a rectangular grid, interpolation is needed after any geometric transformation. Consider a fixed row in the rotated image.

2.1.2. Resolution of the Estimator: The resolution is independent of the number of rows M, provided it is not too small, because it does not affect the position of the peak but only the strength with respect to the off-peak spectral magnitudes. When M is very small, say, less than 32, the peak becomes faint and may be indiscernible. For portraits, it is better to use columns since a larger provides higher angular resolution

2.1.3.Distinguishing Rescaling and Rotation: Both rescaling and rotation use interpolation, leading to detectable peaks in the DFT of the edge map along the row or column direction. These peaks can be used to estimate the interpolation parameters. However, the two operations behave differently in some aspects so that they can be distinguished.

2.1.4.MERITS:

Interpolation operations are performed in image rescaling and rotation, which introduce periodicity in the image. This can be used to estimate the factor of digital image rescaling.

2.1.5.DEMERITS:

Since this perform by comparing the forgery image with original image.

2.2.Forensic Detection of Image Manipulation Using Statistical Intrinsic Fingerprints:Matthew C. Stamm, K. J. Ray Liu, Fellow

In this paper, we show that pixel value mappings leave behind statistical traces, which we shall refer to as a mapping's intrinsic fingerprint, in an image's pixel value histogram. We then propose forensic methods for detecting general forms globally and locally applied contrast enhancement as well as a method for identifying the use of histogram equalization by searching for the identifying features of each operation's intrinsic fingerprint. Additionally, we propose a method to detect the global addition of noise to a previously JPEG-compressed image by observing that the intrinsic fingerprint of a specific mapping will be altered if it is applied to an image's pixel values after the addition of noise.

In this work, we show that with the exception of the identity mapping, pixel value mappings leave behind statistical artifacts which are visible in an image's pixel value histogram.We refer to these artifacts as the intrinsicfingerprint of a pixelvaluemapping. By observing the common properties of the histograms of unaltered images,weare able to build a model of an unaltered image's pixel value histogram. We then use this model to identify diagnostic features of a pixel value mapping's intrinsic fingerprint. Because a number of image processing operations are in essence pixelvalue mappings,wepropose a set of imageforgery detection techniques which operate by detecting the intrinsic fingerprint of each operation. Specifically, we propose methods for detecting general forms globally andlocally applied contrast enhancement, as well as a method for identifying the use of histogram equalization, a commonly used form of contrast enhancement.

2.2.1.Statistical intrinsic fingerprints of pixel value mappings: A number of image processing operations, such as contrast enhancement, either include or can be specified entirely by a pixel value mapping. As is the case with most image processing operations, pixel value mappings leave behind distinct, forensically significant artifacts. These artifacts, which we will refer to as the intrinsic fingerprint of a pixel value mapping m, manifest them primarily in an image's pixel value histogram.

2*.2.2.Detecting contrast enhancement:* In this section, we identify the intrinsic fingerprints of contrast enhancement mappings and use them to develop a set of image forensic techniques capable of detecting if an image has undergone contrast enhancement. While prior image forensic work has studied gamma correction, this work assumes that the forensic examiner knows which specific type of contrast enhancement may have been applied and that the contrast enhancement mapping can be described by a simple parametric equation.

2.2.3.Detecting additive noise in previously jpeg-compressed images: In this section, we present a technique designed to detect the global addition of noise to an image that has previously undergone

JPEG compression. Though this may initially seem to be a fairly harmless operation, additive noise can be used to disguise visual traces of image forgery or in an attempt to mask statistical.

2.2.4.MERITS:

Results indicate that all of the proposed forensic techniques are very useful tools for identifying image manipulations and forgeries.

2.2.5.DEMERITS:

Since this algorithm detect the forgery region by using contrast enhancement method. If the given image was in same contrast, we cannot find the forgery region

2.3.Detecting and Extracting the Photo Composites Using Planar Homography and Graph Cut:Wei Zhang, Xiaochun Cao, Yanling Qu, Yuexian Hou, Handong Zhao, and Chenyang Zhang

In this paper, we propose an automatic fake region detection method based on the planar homography constraint, and an automatic extraction method using graph cut with online feature/parameter selection. Two steps are taken in our method: 1) the targeting step, and 2) the segmentation step. First, the fake region is located roughly by enforcing the planar homography constraint. Second, the fake object is segmented via graph cut with the initialization given by the targeting step. To achieve an automatic segmentation, the optimal features and parameters for graph cut are dynamically selected via the proposed online feature/parameter selection.

In summary, our method has the following advantages compared with previous ones:

1) The planar homography constraint is introduced for the fake region detection as a geometrical method.

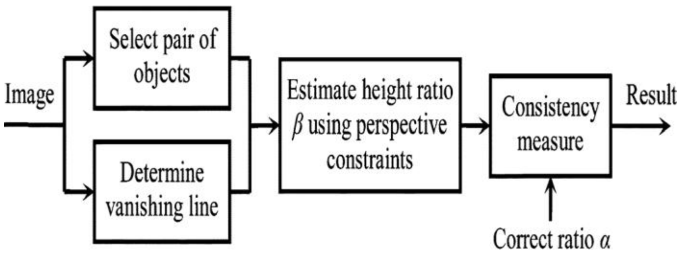
2) Rather than the rough location, precise boundaries of the fake object are extracted.

3) The online feature/parameter selection framework is adopted to improve the performance and automatization of the segmentation process.

3. EXISTING SYSTEM

In Existing they identify the forensic object in the photography.

Our aim is to determine whether two objects in an image have proper relationship in size satisfying the perspective rules. Therefore, we only need to find the ratio of the objects' heights, rather than calculate their absolute heights, which are hard to get since the camera height is generally unavailable. In this, we first estimate Vanishing Line of a Reference Plane.



Then we have to Determine Height Ratio of the two Selected Objects. the block given below shows the steps in perspective constraint.

4. PROPOSED SYSTEM

In this method we propose the method to detect the forensic in the photography. For that here we use the svm classifier for the forensic detection. Initially we identify the illuminant map in the image. We find the face from the photography. For the face detect here we use the violo john method. After face detection we crop the face image and calculate the canny edge and HOG feature. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms. The method extracts invariance to geometric and photometric transformations for object orientation. After that we identify the Statistical analysis of structure Information (SASI). In SASI is the statistical information of the image such as energy, entropy, correlation sum of energy and sum of correlation are calculated. The extracted feature will pass to the SVM classifier for the training. SVM is stands for Support vector machine. It is a binary classifier. It is a kernel based learning classifier. The trained classifier will predict about the image whether it is original or forensic image.

5. MODULES

- Preprocessing
- Face Detection
- LBP feature Descriptor
- GLCM feature
- SVM classifier

5.1.Module Description:

5.1.1.Preprocessing:

Here we convert the image to illuminant map for that here we are using the YCbCr. Y′ is the luma component and C_B and C_R are the blue-difference and red-difference chroma components. Y′ (with prime) is distinguished from Y, which is luminance, meaning that light intensity is nonlinearly encoded based on gamma corrected RGB primaries.

Y′CbCr signals (prior to scaling and offsets to place the signals into digital form) are called YPbPr, and are created from the corresponding gamma-adjusted RGB (red, green and blue) source using two defined constants K_B and K_R as follows:

$$Y' = K_R \cdot R' + (1 - K_R - K_B) \cdot G' + K_B \cdot B'$$
$$P_B = \frac{1}{2} \cdot \frac{B' - Y'}{1 - K_B}$$
$$P_R = \frac{1}{2} \cdot \frac{R' - Y'}{1 - K_R}$$

where K_B and K_R are ordinarily derived from the definition of the corresponding RGB space. (The equivalent matrix manipulation is often referred to as the "color matrix".)

System Architecture:

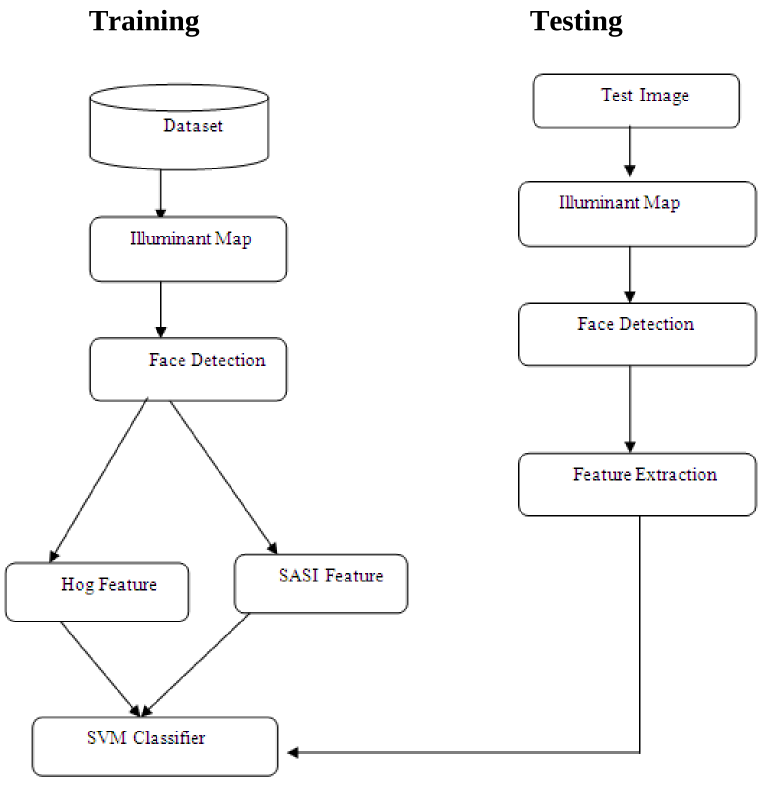


Fig: *Flow diagram*

Here, the prime ′ symbols mean gamma correction is being used; thus R′, G′ and B′ nominally range from 0 to 1, with 0 representing the minimum intensity (e.g., for display of the color black) and 1 the maximum (e.g., for display of the color white). The resulting luma (Y) value will then have a nominal range from 0 to 1, and the chroma (P_B and P_R) values will have a nominal range from -0.5 to +0.5. The reverse conversion process can be readily derived by inverting the above equations.

5.1.2.Face Detection:

Here we use the viola-john face detection method. it identify the face based on the haar features. It is statistical model of the shape of objects which iteratively deform to fit to an example of the object in a new image. The shapes are constrained by the PDM (point distribution model) Statistical shape model to vary only in ways seen in a training set of labeled examples. The shape of an object is represented by a set of points. It aims to match the model to a new image. It works by alternating the following steps:

1) Look in the image around each point for a better position for that point.
2) Update the model parameters to best match to these new found positions

It will match the shape to the new image. It also required Statistical shape model and Model of image structure at each point. The models described below require a user to be able to mark 'landmark' points on each of a set of training images in such a way that each landmark represents a distinguishable point present on every example image.

In order to locate a structure of interest, we must first build a model of it. To build a statistical model of appearance we require a set of annotated images of typical examples. We must first decide upon a suitable set of landmarks which describe the shape of the target and which can be found reliably on every training image.

5.1.3.LBP Feature Extraction:

Local binary patterns (LBP) is a type of feature used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed.

The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbor's value, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).
- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells. This gives the feature vector for the window
- Initially we separate the image as patches. For each patch of image we apply the LBP(Local Binary Pattern).

The LBP operator assigned a label to every pixel of a gray level image. The label mapping to a pixel is affected by the relationship between this pixel and its eight neighbors of the pixel. If we set the gray level image is I, and Z0 is one pixel in this image. So we can define the operator as a function of Z0 and its neighbors, Z1, …, Z8. And it can be written as:

$$T = t\ (Z0, Z0\text{-}Z1, Z0\text{-}Z2, \ldots, Z0\text{-}Z8).$$

However, the LBP operator is not directly affected by the gray value of Z0, so we can redefine the function as following:

$$T \fallingdotseq t\,(Z0-Z1,\ Z0-Z2,\ \ldots,\ Z0-Z8).$$

To simplify the function and ignore the scaling of grey level, we use only the sign of each element instead of the exact value. So the operator function will become:

$$T \fallingdotseq t\,(s(Z0-Z1),\ s(Z0-Z2),\ \ldots,\ s(Z0-Z8)).$$

5.1.4.SASI Feature:

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics.

A GLCM is a matrix where the number of rows and colums is equal to the number of gray levels, G, in the image. The matrix element is the relative frequency with which two pixels, separated by a pixel distance occur within a given neighborhood, one with intensity i and the other with intensity j. One may also say that the matrix element contains the second order statistical probability values for changes between gray levels i and j at a particular displacement distance d and at a particular angle (theta).

A small (5×5) sub-image with 4 gray levels and its corresponding gray level coocrurrence matrix $P(i, j \mid \Delta x = 1, \Delta y = 0)$ is illustrated below.

IMAGE

0	1	1	2	3
0	0	2	3	3
0	1	2	2	3
1	2	3	2	2
2	2	3	3	2

P(i,j;1,0)

	j=0	1	2	3
i= 0	1/20	2/20	1/20	0
1	0	1/20	3/20	0
2	0	0	3/20	5/20
3	0	0	2/20	2/20

Even visually, quantization into 16 gray levels is often sufficient for discrimination or segmentation of textures. Using few levels is equivalent to viewing the image on a coarse scale, whereas more levels give an image with more detail. However, the performance of a given GLCM-based feature, as well as the ranking of the features, may depend on the number of gray levels used.

5.1.4.Texture Features from GLCM:

A number of texture features may be extracted from the STATISTICAL

We use the following notation:

G is the number of gray levels used.

μ is the mean value of P.

μx, μy, σ_x and σ_y are the means and standard deviations of Px and Py. Px(i) is the ith entry in the marginal-probability matrix obtained by summing the rows of P(i, j):

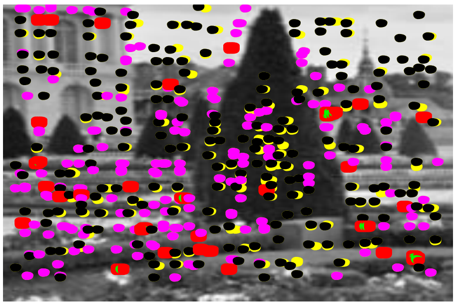
5.1.5.SVM Classifier:

SVM classifier is the one of the supervised classifier. This is one of the Kernel-based techniques which represent a major development in machine learning algorithms. We provide our feature values to the SVM classifier. The classifier will train about the feature. Finally it will classify about the result. The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes.

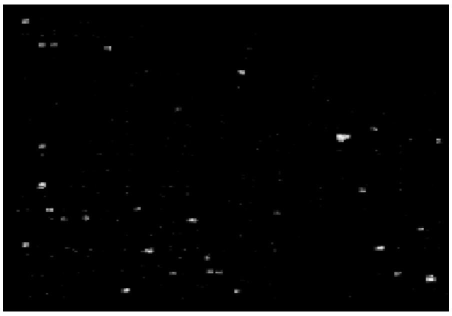
5.2.Results and Screen Shots:

Original image:

Tracing image



Binary image:



Gray scale image

Illuminaation Adjustment

Original Image **Forged Image**

6. CONCLUSION

Here we detect the forensic in the photography. For the detection we extract LBP feature, GLCM feature. And finally we predict the result by SVM classifier. Our method provides the better result than the existing system.

Future Enhancement:

In Future we extract the feature with some other algorithm to improve the performance of our system.

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