# CONTRAST ENHANCEMENT BASED IMAGE FORGERY DETECTION

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**Abstract**— Contrast enhancement is generally used to adjust the global brightness and contrast of digital images. Malicious users perform contrast enhancement for creating a realistic composite images. Nowadays contrast enhancement is used for checking authenticity and originality of images. In this paper two novel algorithms are proposed in-order to detect manipulated digital images involving contrast enhancement. First, we focus on the detection of contrast enhancement applied to JPEG-compressed images. The histogram peak/gap artifacts incurred as a result of the JPEG compression and pixel value mappings are analyzed theoretically and notable by identifying the zero-height gap fingerprints. Second, for identifying the composite image formed by enforcing contrast alteration on both source regions. This paper propose a method to find which type contrast enhancement is affected to the raw image. Also detect contrast enhancement whether the image is affected by any type of noising, with the help of these results we can train the datasets by using neural network and calculate the accuracy of the method.

**Keywords**— Contrast enhancement, Image forgery, Neural networks

## 1. INTRODUCTION

Contrast enhancement is frequently referred to as one of the most important issues in image processing. Currently, image forgeries are widespread on the Internet and other security-related applications such as surveillance and recognition that utilize images are therefore impacted. The event and scene information delivered in images might become no longer believable. In the applications such as law enforcement and news recording, it is also necessary to verify the originality and authenticity of digital images, and make clear the image manipulation history to get more information.

Image enhancement processes consist of a collection of techniques that seek to improve the visual appearance of an image that is better suited for analysis by a human or machine. The term image enhancement also mean as the improvement of an image appearance by increasing dominance of some features or by decreasing ambiguity between different regions of the image. Most of the contrast enhancement methods can be classified into two main categories: intensity-based techniques and feature-based techniques. Forgery is the process of making adapting or imitating objects. Forgery consists of filling in blanks on a document containing a genuine image, or materially altering or erasing an existing image. Instruments of forgery may include bills of exchange, bills of lading, promissory notes, checks, bonds, receipts, orders for money or goods, mortgages, discharges of mortgages, deeds, public records, account books, and certain kinds of tickets or passes for transportation or events. Methods of forgery include handwriting, printing, engraving, and typewriting. The related crime of uttering a forged image occurs when an inauthentic image is intentionally as genuine. Some modern statutes include this crime with forgery.

With the rapid development of digital media editing techniques, digital image manipulation becomes rather convenient and easy. While it benefits to legal image processing, malicious users might use such innocent manipulations to tamper digital photograph images. Currently, image forgeries are widespread on the Internet and other security-related applications such as surveillance and recognition that utilize images are therefore impacted. The event and scene information delivered in images might become no longer believable. In the applications such as law enforcement and news recording, it is also necessary to verify the originality and authenticity of digital images, and make clear the image manipulation history to get more information. To circumvent such a problem, digital forensic techniques have been proposed to blindly verify the integrity and authenticity of digital images.

## 2. RELATED WORKS

S. Bayram, I. Avcubas, B. Sankur, and N. Memon [2] proposed a technique for the detection of doctoring in digital image. Doctoring includes multiple steps i.e. a sequence of basic image-processing operations such as rotation, scaling, smoothing, contrast shift etc. The methodology used is based on the three categories of statistical features including binary similarity, image quality and wavelet statistics. The three categories of forensic features are as follows:
1) Image Quality Measure: These focus on the difference between a doctored image and its original version. The original not being available, it is emulated via the blurred version of the test image.
2) Higher Order Wavelet Statistics: These are extracted from the multi-scale decomposition of the image.

3) Binary Similarity Measure: These measures capture the correlation and texture properties between and within the low significance bit planes, which are more likely to be affected by manipulations.

To deal with the detection of doctoring effects, firstly, single tools to detect the basic image-processing operations are developed. Then, these individual weak detectors assembled together to determine the presence of doctoring in an expert fusion scheme.

M. Stamm and K. Liu [3] proposed a blind forensic algorithm for detecting the use of global contrast enhancement operations on digital images. Proposed work is based on the fact that, gray level histogram of the unaltered images exhibit a smooth contour whereas, gray level histogram of contrast enhanced images shows unsmoothness (peak/gap artifacts). A separate algorithm is proposed to identify the use of histogram equalization, a commonly Implemented contrast enhancement operation. The methodology used is as follows. The methodology used is known as global contrast enhancement detection technique. This algorithms works by seeking out the unique artifacts left behind by histogram equalization. However, the paper specifies only about the detection of global enhancement and not about the local enhancement.

M. C. Stamm and K. J. R. Liu [4] proposed different methods not only for the detection of global and local contrast enhancement but also for identifying the use of histogram equalization and for the detection of the global addition of noise to a previously JPEG-compressed image. The methodologies used are as follows.

1) Detecting globally applied contrast enhancement in image

Contrast enhancement operations are viewed as nonlinear pixel mapping which introduce artifacts into an image histogram. Nonlinear mappings are separated into regions where the mapping is locally contractive. The contract mapping maps multiple unique input pixel values to the same output pixel value. Result in the addition of sudden peak to an image histogram.

2) Detecting locally applied contrast enhancement in image

Contrast enhancement operation may be locally applied to disguise visual clues of image tampering. Localized detection of these operations can be used as evidence of cut-and-paste type forgery. The forensic technique is extended into a method to detect such type of cut-and- paste forgery.

3) Detecting Histogram equalization in image

Just like any other contrast enhancement operation, histogram equalization operation introduces sudden peaks and gaps into an image histogram. The techniques are extended into method for detecting histogram equalization in image.

4) Detecting Noise in image

Additive noise may be globally applied to an image not only to cover visual evidence of forgery, but also in an attempt to destroy forensically significant indicators of other tampering operations. Though the detection of these types of operations may not necessarily pertain to malicious tampering, they certainly throw in doubt the authenticity of the image and its content. The technique for detecting noise is able to detect whether the image is in noise or not, such as speckle noise, Gaussian noise etc.

M. Stamm and K. Liu [5] focuses on recovering the possible information about the unmodified version of image and the operations used to modify it, once image alterations have been detected. An iterative method based on probabilistic model is proposed to jointly estimate the contrast enhancement mapping used to alter the image as well as the histogram of the unaltered version of the image. The probabilistic model identifies the histogram entries that are the most likely to occur with the corresponding enhancement artifacts.

G. Cao, Y. Zhao, and R. Ni [6] present a blind method for the detection of gamma correction, a special type of contrast enhancement. The technique used is based on the histogram characteristics that are measured by patterns of the peak gap features. These peak gap features for the gamma correction detection are distinguished by the precomputed histogram of images.

## Proposed Contrast Enhancement Detection Algorithm

The proposed contrast enhancement detection algorithm as follows.

1) Get the images normalized gray level histogram h(x).

2) Detect the bin at k as a zero-height gap bin if it satisfies:

$$h(k) = 0$$

$$\min\{h(k-1),\, h(k+1)\} > \tau$$

$$\sum_{x=k-w_1}^{k+w_1} h(x) > \tau$$

Here, the first sub-equation assures that the current bin is null. To define a gap bin, the second sub-equation keeps two neighboring bins larger than the threshold, as shown in Fig. 1. To exclude the zero-height gap bins which may be incorrectly detected in histogram trail-ends, the average of neighboring 2w1 + 1 bins should be larger than, as constrained by the third sub equation. Experiments show that w1 =3 and 0:001 are appropriate. Note that we focus on the detection of isolated zero-height gap bins but not connected bins, which are rarely present in the middle of histograms.

3) Count the number of detected zero-height gap bins, denoted by Ng. If it is larger than the decision threshold, contrast enhancement is detected, else not. In the proposed system it detects image forgery based on contrast enhancement and also train the images in the database. It is an efficient method to find images is a manipulated one or not. Using neural network it trains and built the database.

## 3. SYSTEM DESIGN

A novel algorithm is proposed to identify the source-enhanced composite image created by enforcing contrast adjustment on either single or both source regions. The outline of our technique is shown in Fig 1. Since positional distribution of the peak/gap bins incurred by contrast enhancement is unique to the involved pixel value mapping, such positional information could serve as fingerprinting feature for identifying different contrast enhancement manipulations. Consistency between the peak/gap artifacts detected in different regions is checked for discovering composite images.

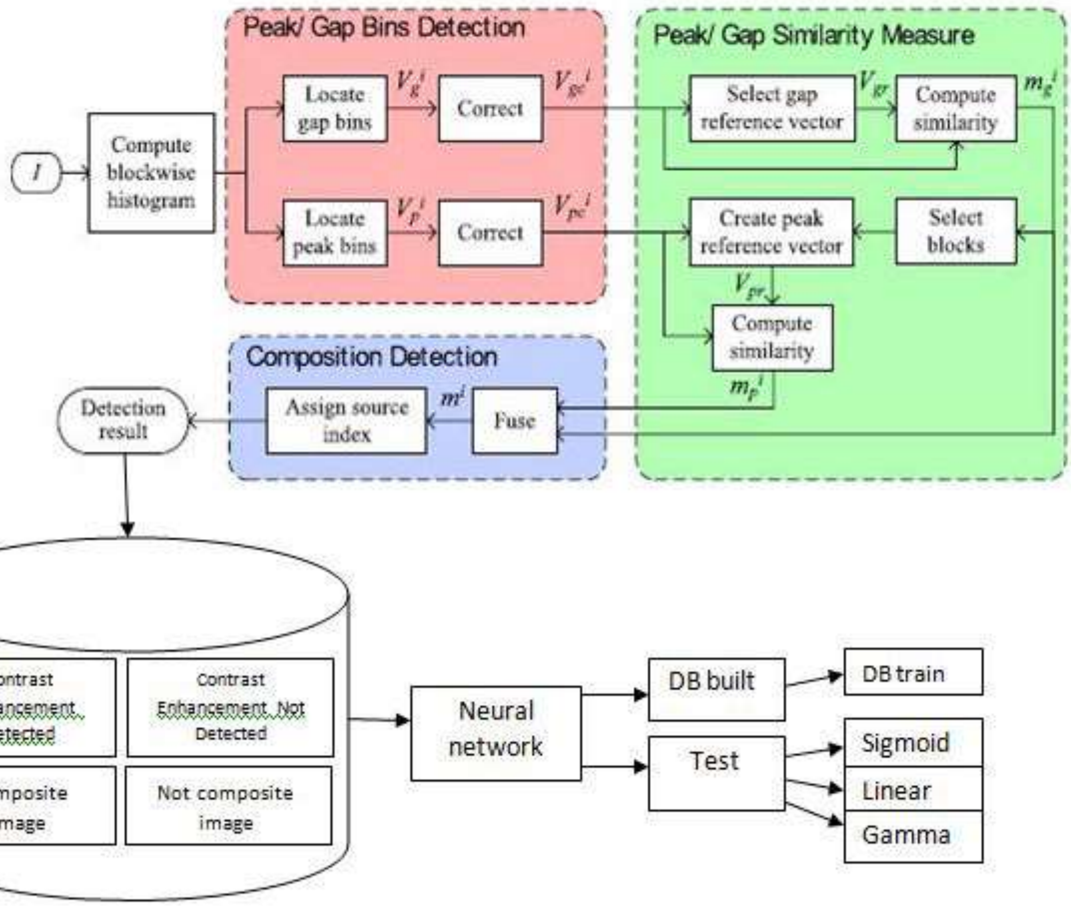



Fig 1: Flowchart of the proposed composite image detection technique.

3.1 Block wise Peak/Gap Bins Location

To locate composition, the test image I is first divided into non overlapping blocks. For the i -th block, peak/gap bins in its gray level histogram are located as follows. Here and below, i = 1, 2,… Nb, where Nb is the number of divided blocks.

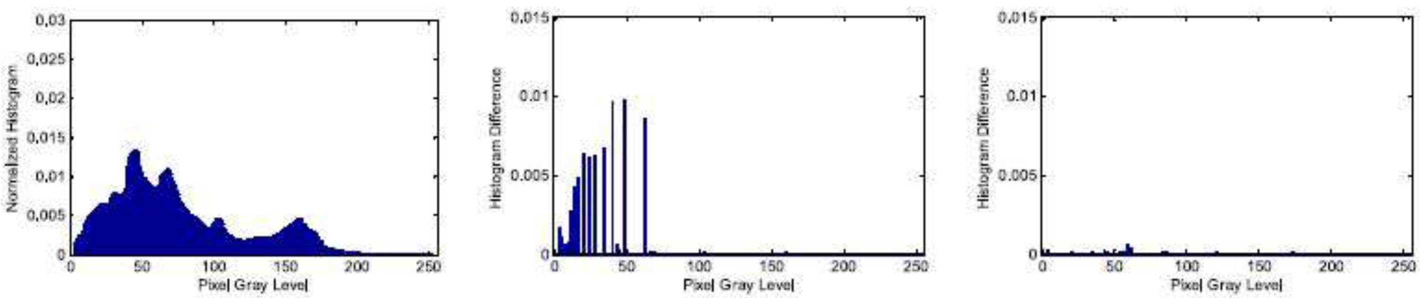
1) Gap Bins Location: The zero-height gap bins are detected. The position of detected gap bins is labelled as Vig = [Vig (0), Vig (1), Vig (k), V Ig (255)], where Vig (k) = 1, if the bin at k is a gap; Vig (k) = 0, otherwise.

2) Peak Bins Location: Peak bins which behave as impulse noise can be located by median filtering. Specifically, the gap bins are first filled with the average of neighboring bins, then median filtering is applied to the gap-filled histogram. As shown in fig 2, the filtered histogram possesses a smooth contour. Lastly, peak positions are located by thresholding the difference between the gap-filled histogram and its filtered version. The histogram differences for the enhanced and primary example images are shown in Fig. 2(b) and (c), respectively. It can be seen that peak bins are not detected in the primary image. Record the detected peak positions as Vip= [Vip (0), Vip (1),, Vip(k),, Vip (255)], where Vip(k) =1 refers to a peak. The peak/gap bins which are theoretically computed from contrast enhancement mapping may not appear since the histogram is too narrow to cover such bin positions. To address such a factor, Effective Detection Range (EDR) for the i -th block wise peak/gap position vector, is defined as the set of gray levels around which the histogram bins are not all zeros. In other words, the histogram bins at the gray levels out of EDR are zeros. Because of the narrow histograms incurred by low resolution, EDR of most position vectors actually contains limited gray levels. Specifically, we apply a simple and strict threshold- based binarization to Cg = Σ V ig / Nb The detected co-existing gap positions are recorded as Vg =

[Vg(0), Vg(1),, Vg(k),, Vg(255)], where Vg(k) = 1, if Cg(k) is larger than the threshold; Vg(k) = 0, otherwise. To eliminate the gap bins which might not be caused by contrast enhancement, the corrected gap position vector Vig, is generated as

$$V_{gc}^{\,i} = V_g^{\,i} \odot V_g,$$

$\odot$ where denotes Hadamard product, k = 0, 1, 2,…. 255. Similarly, the corrected peak position vector Vipc can also be obtained.




(a) (b) (c)

Fig 2: Peak bins location.(a) Filtered gap-filled version of the histogram; histogram difference for the (b) enhanced and (c) unenhanced image.

3.2 Gap Based Similarity Measure

To discriminate two source regions, we should first set a reference position vector for either one. Then each block can be classified by the similarity between its position vector and the reference one. It is reasonable to deem that the blocks with approximate similarity come from the same source image. The reference position vector should not be selected from splicing boundary. Fortunately, the block with the largest number of zero-height gap bins is believed to locate within one source region. In boundary blocks, the interaction between the pixels from different source regions makes the number of zero height bins decrease. As a result, the reference gap position vector for its located source region (marked as S1) can be set as V rg = V^kgr where.

$$k = \underset{i\in\{1,2,\ldots,N_b\}}{\arg\max} \left(\|V_{gc}^i\|\right).$$

Here, ‖ ‖denotes 1-norm of a vector. EDR of the reference gap position vector. To measure the overall similarity between the gap position vectors V ^c ig and Vgr, each gap-involved pair V^ igc and Vgr (k) should be investigated firstly. Since the histogram at the gray levels out of EDR does not deliver any effective peak/gap information left by contrast enhancement, the element pairs in the intersection of two EDRs are used to measure the similarity. As shown in Fig. 3, there exist three possible correspondences for a gap-involved pair. They are,

$$① \; V_{gr}(k) = 1, \quad V_{gc}^i(k) = 1;$$

$$② \; V_{gr}(k) = 0, \quad V_{gc}^i(k) = 1;$$

$$③ \; V_{gr}(k) = 1, \quad V_{gc}^i(k) = 0.$$

We can see that the gap-involved pair is matched in the case but mismatched in. The overall similarity between V^igc and Vgr is determined by such three cases frequency. In the intersection between two EDRs, the ratio between the number of matched pairs and that of total gap-involved pairs is defined as the similarity. The pair is completely matched in the case. The more pairs occur as such, the more similar the two gap position distributions are. In the case, the detected gap is not marked in the reference vector. In the case, the gap in the reference vector is absent in the unlabeled histogram.

Both and attribute to the different contrast enhancement mapping applied to the image region out of the reference block. Based on the above analyses, the similarity between V^ igc and Vgr denoted by mig, can be defined as the below equation. Here,

$$m_g^i = \frac{\sum\limits_{k\in\Omega_i\cap\Omega_{gr}} V_{gc}^i(k)\cdot V_{gr}(k)}{\sum\limits_{k\in\Omega_i\cap\Omega_{gr}} V_{gc}^i(k)\cdot V_{gr}(k) + \overline{V_{gc}^i}(k)\cdot V_{gr}(k) + V_{gc}^i(k)\cdot \overline{V_{gr}}(k)},$$

When no gap-involved pair is m^i g= 1.We can see that m^i g becomes larger if more gaps co-exist. m^i g approaches the maximum 1 if all gaps are matched, and decreases to 0 if all gap-involved pairs behave as . Correspondingly, the possibility that the two blocks undergo the same pixel value mapping ranges from the largest to the smallest.

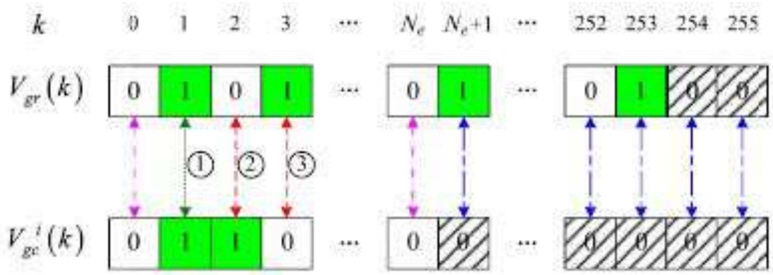



Fig 3: Correspondence between Vgr and V^ igc. Here, EDRs of Vgr and V^i gc respectively. The positions out of EDR are marked by the box with shadow. The gap-involved pair is matched in the case and mismatched in the cases.

### 3.3 Peak Based Similarity Measure

Since the image block usually owns a narrow histogram, the theoretical gap bins might be unavailable in not a few blocks. Such blocks cannot be assigned to either source region merely based on the gap information. However, the narrow histogram without gap bins might carry with peak bins. As such the peak bins should also be exploited to identify mappings. The reference peak position vector Vpr is created by combining the peak position vectors which are more possible from the source region of Vgr, namely S1. Such creation of Vpr is reliable since the collected peak information is relatively accurate. Specifically, we have

$$V_{pr}(k) = \ell\left(\sum_{n \in \mathrm{N}_R} V_{pc}^{n}(k) > 0\right).$$

Here, k = 0, 1, 2,, 255.l (_) is the indicator function.NR = i n mig > tg where tg is the threshold used to candidate block. As defined m^i g in (8), the similarity between V ^i gc and Vgr marked as m^i p, is defined in the same form by replacing the gap variables with the corresponding peak ones. If no peak involved pair exists in EDR intersection, we mark m^i p=-1 select the candidate blocks.

### 3.4 Similarity Maps Fusion for Composition Detection

Before fusion, m^ig=-1 and m^ip=-1 the block wise similarities are updated by averaging the available neighboring effective measurements. The resulting similarity for the i -th unlabeled block, denoted by mi, can be generated by fusing the peak/gap based similarities.

$$m^{i} = \left(m_{g}^{i} + m_{p}^{i}\right)/2.$$

When m^ig=-1 or m^ip=-1: mi=max (m^ig, m^ip).when mi=-1 occurs scarcely in both-source-enhanced composite images. If all the blocks in an unsaturated region own mi=-1 while the blocks out of the region have mi>t, the test image can be identified as a single-source-enhanced composite image. Otherwise, each block is classified as: 1) if mi t, contrast enhancement mapping applied to S1 is detected; 2) if mi<t, a different contrast enhancement mapping applied to the other source region is detected. Hence, the both-source enhanced composite image is detected if two different mappings are detected in two complementary regions, respectively. The threshold t is experimentally set as 0.2.
Using neural network this project detects which type of contrast enhancement applied to the images. According to contrast variation enhancements are classified into 3 main categories:

1) Linear contrast enhancement
2) Sigmoid contrast enhancement
3) Gamma contrast enhancement.

1) Linear contrast enhancement

Linear contrast stretching (LCS) is an enhancement method performed on an image for locally adjusting each picture element value to improve the visualization of structures in both darkest and lightest portions of the image at the same time. This type referred a contrast stretching, linearly expands the original digital values of the remotely sensed data into a new distribution. By expanding the original input values of the image, the total range of sensitivity of the display device can be utilized. Linear contrast enhancement also makes subtle variations within the data more obvious. These types of enhancements are best applied to remotely sensed images with Gaussian or near-Gaussian histograms, meaning, all the brightness values fall within a narrow range of the histogram and only one mode is apparent.

2) Sigmoid contrast enhancement

Sigmoid contrast enhancement is based on modifying the appearance of an image by controlling the input pixel values via an equation depending on the sigmoid function. This enhancement adjust the shadows and highlights in poor contrast images as well as the signal to noise ratio. The sigmoid function has the characteristics that it is a smooth continuous function, the function outputs within the range 0 to 1, mathematically the function is easy to deal with; it goes up smoothly and kindly.

3) Gamma contrast enhancement

Gamma is an important but seldom understood characteristic of virtually all digital imaging systems. It defines the relationship between a pixel's numerical value and its actual luminance. Without gamma, shades captured by digital cameras wouldn't appear as they did to our eyes (on a standard monitor).

Neural network is a nonlinear mapping system whose structure is loosely based on principles of the real brain. The whole network is build up with simple processing units, structures of those can be seen. The unit is a simplified model of a real neuron. Its parts are the input vector x whose containing information is manipulated by the weighted nodes by weigh vector w. The weight change in each layer is done with steepest descent algorithm. The back-propagation algorithm is carried out in the following steps:

1. Select a training pair from the training set; apply the input vector to the network input.
2. Calculate the output of the network.
3. Calculate the error between the network output and the desired output (the target vector from the training pair)
4. Adjust the weights of the network in a way that minimizes the error.
5. Repeat the steps 1 through 4 for each vector in the training set until the error for the entire set is acceptably low.

### ACKNOWLEDGMENT

This project would never have been successful to this point if it weren't for the dedication put in by many minds selflessly. First, I thank GOD, THE ALMIGHTY for showering his abundant blessings upon me for the fulfillment of this project. I express my sincere thanks to my project guide Ms.Jyothirmayi Devi, Assistant Professor in Computer Science Engineering, for guiding me in my work and providing timely advices and valuable suggestions. This humble endeavor wouldn't have become a success without the constant support, inspiration and blessings from my parents.

## CONCLUSION

The proposed contrast enhancement based image manipulation methods could work particularly well when contrast enhancement is performed as the last step of manipulation. In the future work, I would try to improve the robustness of such methods against post processing, such as JPEG compression. It is also essential to enhance the security rather than forensics. In this paper we proposed an iterative algorithm to jointly estimate an images unaltered pixel value histogram as well as the contrast enhancement mapping used to modify the image given only a contrast enhanced version of the image. We used a probabilistic model of an images histogram to identify the histogram entries most likely to correspond to contrast enhancement artifacts. We then used this model along with knowledge of how contrast enhancement modifies an images histogram to obtain our unaltered histogram and contrast enhancement mapping estimates. Simulation results indicate that our algorithm is capable of providing accurate estimates even when nonstandard forms of contrast enhancement are applied to an image.

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