BLIND FORENSICS OF CONTRAST ENHANCEMENT IN DIGITAL IMAGES

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ABSTRACT

Digital images have seen increased use in applications where their authenticity is of prime importance. This proves to be problematic due to the widespread availability of digital image editing software. As a result, there is a need for the development of reliable techniques for verifying an image's authenticity. In this paper, a blind forensic algorithm is proposed for detecting the use of global contrast enhancement operations to modify digital images. Furthermore, a separate algorithm is proposed to identify the use of histogram equalization, a commonly implemented contrast enhancement operation. Both algorithms perform detection by seeking out unique artifacts introduced into an image's histogram as a result of the particular operation examined. Additionally, results are presented showing the effectiveness of both proposed algorithms.

Index Terms— Multimedia forensics, blind forensics, contrast enhancement, histogram equalization.

1. INTRODUCTION

In recent years, digital images have come to play an important role in news media, law enforcement, and military applications where their authenticity is of prime importance. This proves to be problematic due to the widespread availability of digital image editing software. In the past, extrinsic methods such as semi-fragile digital watermarking have been proposed as a means to detect evidence of image alterations [1]. These means of image authentication are limited by the requirement that a digital signature must be inserted into an image by a trusted source before any alterations occur. However, in many practical applications either no signature has been inserted, or the source of the signature may not be trusted. As a result, there is an increasing need for forensic methods to identify image alterations without relying on the insertion of an extrinsic signature.

Blind forensic methods, or methods that make no use of outside information about an image or its history, provide a solution to this problem. These methods operate under the premise that the only information available is the image of unknown authenticity itself [2]. Evidence of image alterations can be gathered by modelling intrinsic properties of an image, then using these properties to identify tampering. Similarly, a detection scheme can be designed by identifying traceable statistical artifacts left behind by an image altering operation.

In order to determine if an image has undergone any form of alteration, the use of a wide variety of operations must be tested for. Existing image forensics work has dealt with the detection of resampling [3] [2], luminance nonlinearities [2], and the tracing of an image's compression history[4] [5]. In addition, methods have been proposed to detect the use of a tamper filter, as well as estimate its coefficients by exploiting properties of color filter array interpolation [6] [7]. While the parameterization of gamma correction has been studied in [2] and [8], a detection scheme is not fully developed and tested. Furthermore, no prior work has addressed the problem of blindly detecting more general contrast enhancement operations.

In this paper, we propose a blind forensic algorithm for detecting the use of global contrast enhancement operations on digital images. Contrast enhancement operations can be viewed as nonlinear pixel mappings which introduce artifacts into an image's histogram. By modeling digital images as the output of a digital capture device (i.e. excluding computer generated images), we may infer several properties of an unaltered image's histogram, which can be used to detect contrast enhancement artifacts. Furthermore, we propose an algorithm for identifying the use of histogram equalization, a commonly implemented contrast enhancement operation. Again, this algorithm operates by seeking out the unique artifacts left behind by histogram equalization.

2. SYSTEM MODEL

We model digital images as the output of the following image capture process. First, the color values of a real world scene are sampled by using an electronic device to measure the average reflected light intensity over each pixel's area. Inherent in this process is the addition of some zero mean observational noise, largely due to noise within the electronic sensor. The light intensity measurements are then quantized, after which some postprocessing may occur. Finally, the output of this process is stored as the unaltered image.

For any digital image, a histogram $h(x)$ of its pixel values x can be calculated by creating B equally spaced bins which span the range of possible pixel values and tabulating the number of pixels whose value falls within the range of each bin. For the purposes of this work, we consider pixel values to consist of integers on the range of 0 to 255, and images to be grayscale in nature. Unless otherwise specified, we assume that all image histograms are calculated using 256 bins so that each bin corresponds to a unique pixel value.

The effect of sampling on an image's histogram can by understood by examining the scenario depicted in Fig. 1. In this figure, a scene consisting of two different color regions is depicted. The border between these two regions does not align with the pixel boundaries of the digital capture device. Because of this, pixels lying along the color border cover areas containing both color values present. As a result, these observed pixel values will lie somewhere in between those corresponding to each true color. This will effectively 'smooth out' an image's histogram

Several other phenomena contribute to the 'smoothness' of an image's histogram as well. The complex nature of most natural and man made lighting environments rarely result in a real world scene consisting several distinct colors with no shading. Instead a continuum of color values and illumination levels exist in real world scenes. In addition, if the observational noise present in the image capture process is sufficiently large, some pixels will incorrectly be observed as a slightly higher or lower pixel value than the correct

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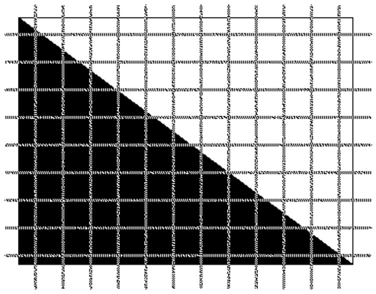

Fig. 1. Sampling effects example.

one.

We model the histogram of an unaltered image as a digital function which approximately conforms to a smooth envelope. It is worth explicitly stating that our model assumes that if $h(x) \gg 0$, then $h(x-1) \neq 0$ and $h(x+1) \neq 0$, or in other words an unaltered image's histogram should not abruptly transition to or from zero. This 'smooth' histogram model plays an important role in both of our proposed detection algorithms.

3. PROPOSED CONTRAST ENHANCEMENT DETECTION ALGORITHM

A global contrast enhancing operation $T(x)$ can be viewed as a nonlinear mapping of pixel values, followed by quantization. These nonlinear mappings can be separated into regions where the mapping is locally contractive or expansive. A mapping f is *contractive* if $d(f(x), f(y)) < d(x,y)$ and *expansive* if $d(f(x), f(y)) > d(x,y)$, where $d(\bullet)$ is some distance measure. When followed by quantization, contractive mappings can map multiple unique input pixel values to the same output value, resulting in the addition of sudden peaks to an image's histogram. Similarly, expansive mappings can cause output pixel values to be skipped over, resulting in gaps in an image's histogram. These effects are clearly seen in the plots at the top of Fig. 2 which show the histograms of an unaltered image and an image that has undergone contrast enhancement.

The peaks and gaps introduced into an image's histogram are contrast enhancement artifacts which we use to perform detection. To do this, we exploit the fact that the Fourier transform of an unaltered image's histogram $H(\omega)$ should be strongly low pass in accordance with the smooth histogram model discussed in the previous section. The sudden peaks and gaps introduced into $h(x)$ as a product of contrast enhancement result in the addition of a high frequency component to $H(\omega)$ as can be seen in the bottom two plots in Fig. 2. Our detection algorithm operates by obtaining a weighted measure F of an image histogram's high frequency component and performing a threshold test to determine if contrast enhancement has occurred.

There does exist one class of naturally occurring unaltered images, which we will refer to as *high end* or *low end saturated*, which result in an $H(\omega)$ with a substantial high frequency component. High end saturation occurs when an image is captured under bright lighting conditions and many of the observed light intensities lie well above the cutoff for the highest quantization level. This results in a substantial number of pixels taking on a value of 255, thus creating a sharp peak which resembles a unit impulse. Similarly, low end saturation arises in images taken in dark lighting environments and corresponds to an impulsive peak at the pixel value 0. This is prob-

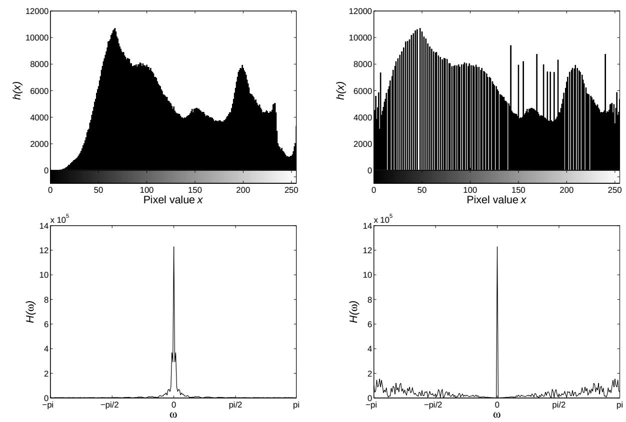

Fig. 2. Top Left: Histogram of an unaltered image. Bottom Left: Magnitude of the Fourier transform of the unaltered image's histogram. Top Right: Histogram of an image which has undergone histogram equalization. Bottom Right: Magnitude of the Fourier transform of the equalized image's histogram.

lematic due to the fact that the Fourier transform of an impulse is a constant function, which will in turn lead to a large value of F and bias the detector towards deciding that contrast enhancement has occurred. To combat this effect, we premultiply $h(x)$ by a pinch off function $p(x)$ to obtain $g(x)$ as follows

$$g(x) = p(x)h(x) \tag{1}$$

$$p(x) = \begin{cases} \frac{1}{2} - \frac{1}{2}\cos\left(\frac{\pi x}{N_p}\right) & x \leq N_p \\ \frac{1}{2} + \frac{1}{2}\cos\left(\frac{\pi(x-255+N_p)}{N_p}\right) & x \geq 255 - N_p \\ 1 & else \end{cases} \tag{2}$$

where the width of the pinch off region N_p is typically around 4 pixels. This has the effect of deemphasizing any possible impulsive components due to saturation in $g(x)$.

We use $g(x)$ to calculate the high frequency measure F according to the formula

$$F = \frac{1}{N} \sum_{\omega} |\beta(\omega) G(\omega)| \tag{3}$$

where N is the total number of pixels in the image, $G(\omega)$ is the Fourier transform of $g(x)$, and $\beta(\omega)$ is a weighting function which takes values between 0 and 1. The purpose of $\beta(\omega)$ is to deemphasize low frequency regions of $G(\omega)$ where nonzero values do not necessarily correspond to contrast enhancement artifacts. In this work, we use the simple cutoff function:

$$\beta(\omega) = \begin{cases} 1 & |\omega| \geq c \\ 0 & |\omega| < c \end{cases} \tag{4}$$

where c is a user specified cutoff frequency. A *threshold test* is then performed, with values of F greater than the decision threshold η corresponding to the detection of contrast enhancement.

The proposed contrast enhancement detection algorithm can be summarized as follows:

1. Obtain the image's histogram, $h(x)$.
2. Calculate $g(x)$ using (1).
3. Transform to the frequency domain and obtain the high frequency measure F according to (3).
4. Apply a threshold test to determine if contrast enhancement has occurred.

4. PROPOSED HISTOGRAM EQUALIZATION DETECTION ALGORITHM

If contrast enhancement is performed using histogram equalization, a unique set of traceable artifacts are left behind in addition to those previously discussed. To understand what these artifacts are, we must first briefly consider how histogram equalization is performed. Histogram equalization attempts to increase the contrast of a digital image by generating a mapping such that the histogram of the output image is approximately uniformly distributed. This is accomplished using the following mapping

$$T(x) = round\left[255\sum_{y=0}^{x}\frac{h(y)}{N}\right] \tag{5}$$

where N is the total number of pixels in the image. Our proposed histogram equalization detection algorithm operates by determining the distance of an image's histogram from a uniform distribution.

Histogram equalization, like any other contrast enhancement operation, introduces sudden peaks and gaps into an image's histogram. This makes detection in the pixel domain rather problematic, because if we measure the distance of the histogram from a uniform distribution through some simple metric D' such as

$$D' = \sum_x \mid h(x) - \frac{N}{255} \mid \tag{6}$$

the peaks and gaps introduced will *increase* the value of D'. Detection is in fact better suited for the frequency domain, where the artifacts unique to histogram equalization can be separated from the artifacts which arise from the use of any general contrast enhancement operation.

The frequency domain representation of a constant function is an impulse $\delta(\omega)$ centered at $\omega = 0$. Using this fact, we obtain a frequency domain measure of the distance D of an image's histogram from a uniform distribution according to the formula

$$D = \frac{1}{N}\sum_{\omega}\left(\delta(\omega) - |H(\omega)|\right)\alpha(\omega) \tag{7}$$

Here $\alpha(\omega)$ is a weighting function used to deemphasize high frequency regions of $H(\omega)$. This is necessary because as a contrast enhancing operation, histogram equalization will add a high frequency component to $H(\omega)$, thus artificially increasing the value of D. If this effect is not properly compensated for with $\alpha(\omega)$, several missed detections could occur. In this work we use

$$\alpha(\omega) = exp(-r|\omega|) \tag{8}$$

where r is a user specified parameter.

As discussed before high and low end saturated images create detection problems due to the constant offset they add in the frequency domain. To mitigate this problem, we exploit histogram equalization artifacts unique to these types of images. For low end saturated images, we may safely assume that the impulsive nature of the histogram will cause the number of pixels in the lowest bin to be greater than $\frac{2N}{255}$. When histogram equalization is performed, the input gray level $x = 0$ is mapped to an output value of $T(0) \geq 2$ because

$$\begin{aligned} T(0) &= round\left[255\sum_{y=0}^{x=0}\frac{h(y)}{N}\right] \\ &\geq round\left[255\left(\frac{2}{255}\right)\right] = 2 \end{aligned} \tag{9}$$

We may therefore conclude that histogram equalization has occurred if $h(x') \geq \frac{2N}{255}$ and $x' \geq 2$, where x' is the lowest pixel value for which $h(x') \geq 0$.

Similarly, for high end saturated images we can assume that $h(255) \geq \frac{2N}{255}$. When histogram equalization is performed, the input gray level $x = 254$ will be mapped to $T(254) \leq 253$ according to

$$\begin{aligned} T(254) &= round\left[255\sum_{y=0}^{x=254}\frac{h(y)}{N}\right] \\ &= round\left[255\left(1 - \frac{h(255)}{N}\right)\right] \\ &\leq round\left[255\left(\frac{2}{255}\right)\right] = 253 \end{aligned} \tag{10}$$

Using this information, we can conclude that histogram equalization has occurred if $h(255) \geq \frac{2N}{255}$ and $x'' \leq 253$, where x'' is the largest value of x such that $x'' < 255$ and $h(x'') > 0$. We refer to detection by this means as the *saturated image histogram equalizataion test*.

The proposed histogram equalization detection procedure can be summarized as follows:

1. Obtain the image's histogram, $h(x)$.
2. Perform the saturated image histogram equalization test, where histogram equalization is determined to have occurred if $h(x') \geq \frac{2N}{255}$ and $x' \geq 2$, or $h(255) \geq \frac{2N}{255}$ and $x'' \leq 253$.
3. If histogram equalization is not yet detected, calculate D using (7).
4. Determine if histogram equalization has occurred by comparing D to some threshold η, where $D < \eta$ corresponds to detection.

5. SIMULATION AND RESULTS

To evaluate the performance of each detection algorithm, an image database was compiled consisting of 341 images captured using several different digital cameras. These images consist of a variety of different subjects, ranging from landscapes to buildings to people, and were taken under varying lighting conditions.

5.1. Contrast Enhancement Detection

In order to test the contrast enhancement detection algorithm, each image was altered using the power law transformation

$$T(x) = 255\left(\frac{x}{255}\right)^{\gamma} \tag{11}$$

with γ values ranging from 0.5 to 2.0. Additionally, each image was subjected to the mapping displayed at the top left of Fig. 3, which was designed to bring out detail in the brightest and darkest regions of each image. These altered images were then combined with the original set of images to form a test database of 4092 images. The proposed detection algorithm was used to determine if each image in the test database had undergone some form of contrast enhancement. In this simulation, $\beta(\omega)$ was chosen to be of the form specified in (4), with the cutoff parameter parameter $c = 7\pi/8$. The probabilities of detection P_d and false alarm P_{fa} were determined for a given threshold η by calculating the percent of correctly classified altered images and the percent of incorrectly classified unaltered images respectively. These probabilities were then used to construct a series of receiver operating characteristics (ROC) curves.

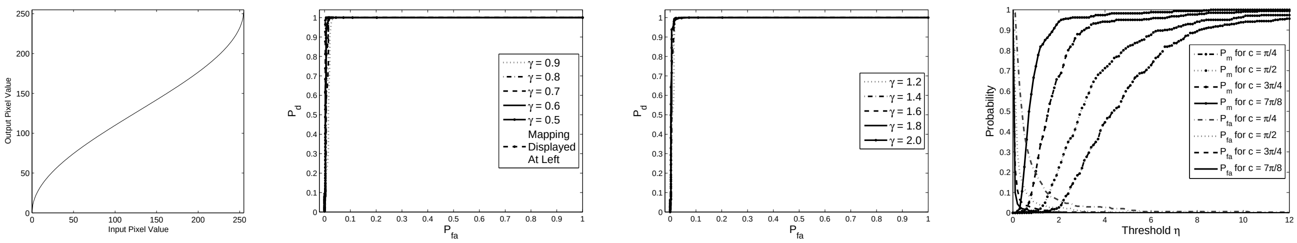

Fig. 3. Simulation results for the contrast enhancement detection scheme. Far Left: Additional contrast enhancement mapping used in the simulation. Center Left: ROC curves obtained for images altered by a power law transformation with $0.5 \leq \gamma \leq 0.9$, as well as the mapping displayed in the top left. Center Right: Additional ROC curves obtained for images altered by a power law transformation with $1.2 \leq \gamma \leq 2.0$. Far Right: Probabilities of missed detection and false alarm vs. detection threshold η for images altered by a power law transformation with $\gamma = 0.6$.

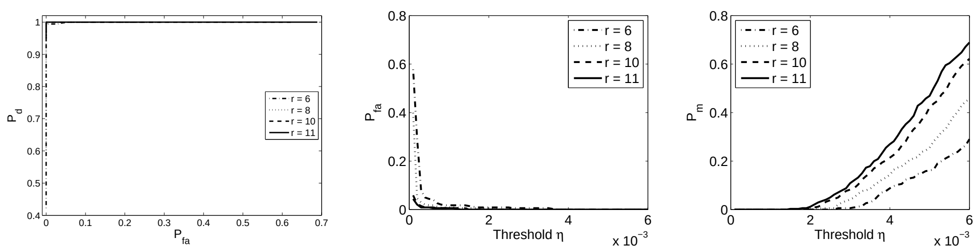

Fig. 4. Simulation results for the histogram equalization detection scheme. Left: ROC curve. Center: Probability of missed detection vs. detection threshold. Right: Probability of false alarm vs. detection threshold.

Fig. 3 shows the ROC curves obtained by the proposed detection algorithm. Additionally, Fig. 3 contains a plot displaying the P_{fa} and P_m (probability of missed detection) with respect to the the decision threshold for different values of the cutoff parameter c when the images were manipulated with $\gamma = 0.6$. As can be seen from the ROC curves, the detection algorithm performs extremely well against all values of γ tested, as well as the mapping displayed at the far left section of Fig. 3. It should be noted that in every case, a P_d of 0.99 was achieved with a P_{fa} of roughly 0.03 or less. Furthermore, the plot of P_{fa} and P_m vs. η indicates that performance improves as c is increased, with the best performance obtained using the largest value of c for which the algorithm was tested. This reinforces the notion that for unaltered images $H(\omega)$ is a strongly lowpass signal, and that contrast enhancement introduces a high frequency component to $H(\omega)$.

5.2. Histogram Equalization Detection

To test the histogram equalization detection algorithm, a setup similar to the one for test the contrast enhancement detection algorithm was used. Each unaltered image was subjected to histogram equalization using (5), then the equalized images and the unaltered originals were combined to form a test database of 682 images. The proposed histogram equalization detection algorithm was used with to determine if each image had undergone histogram equalization. This was performed multiple times using $\alpha(\omega)$ as defined in (8) with r taking values between 6 and 11. The values of P_d and P_{fa} were calculated in the same manner as was used when evaluating the contrast enhancement detection algorithm.

Plots showing the ROC curves obtained for each value of c used, as well as P_{fa} and P_m with respect to η are shown in Fig. 4. When r was chosen to be 10 or 11, perfect detection ($P_d = 1$ with $P_{fa} = 0$) was obtained using the threshold value $\eta = 1.5$. In addition, near perfect detection was achieved

6. CONCLUSION

In this work we propose two new blind forensic algorithms to detect image alterations in the form of global contrast enhancement operations in general, and histogram equalization specifically. We construct a model for the histogram of an unaltered image, and use properties of this model to detect alteration artifacts left behind by both considered operations. Through simulation, we show the efficacy of both detection algorithms, obtaining $P_d > 0.99$ with a corresponding $P_{fa} \leq 0.03$ using our contrast enhancement detection algorithm and perfect detection using our histogram equalization detection algorithm.

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