ACE - An Effective Anti-forensic Contrast Enhancement Technique

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***Abstract*—Detecting Contrast Enhancement (CE) in images and anti-forensic approaches against such detectors have gained much attention in multimedia forensics lately. Several contrast enhancement detectors analyze the first order statistics such as gray-level histogram of images to determine whether an image is CE or not. In order to counter these detectors various anti-forensic techniques have been proposed. This led to a technique that utilized second order statistics of images for CE detection. In this paper, we propose an effective anti-forensic approach that performs CE without significant distortion in both the first and second order statistics of the enhanced image. We formulate an optimization problem using a variant of the well known Total Variation (TV) norm image restoration formulation. Experiments show that the algorithm effectively overcomes the first and second order statistics based detectors without loss in quality of the enhanced image.**

***Index Terms*—Contrast Enhancement, Anti-Forensics, Convex optimization, Second order statistics.**

I. INTRODUCTION

IMAGE and video editing has become increasingly easy and sophisticated, that forgery can be performed without leaving any significant visual artifacts. It is of utmost importance for law enforcement agencies to authenticate image/video provided as evidence. Researchers in the field of multimedia forensics have proposed various techniques ([1], [2], [3] and [4]) to identify different kinds of forgery. Given their targeted nature of forgery detection various 'double compression' detection techniques for images [2] and videos [5] were proposed. These techniques assume that if an image is compressed twice, it might be tampered. This assumption is too generic and research recently started concentrating on signal processing operation detection rather than double compression detection.

Generally image forgery is followed by an enhancement technique [6] that enhances the visual quality of the image and/or hide the artifacts left by the forgery operation. Enhancement operations include filtering operations such as low pass, high pass and non linear median filtering [6]. It also includes contrast enhancements (CE) such as Gamma Correction (GC) and Histogram Stretching (HS) [7]. However, the enhancement operations by itself will leave some artifacts. This is exploited by various researchers in the forensic community to detect such malicious operations ([6], [8] and [9]). Identifying these enhancements involve determining the subtle statistical changes in the image caused by these operations [10]. Recently, anti-forensic techniques are being developed, that perform these enhancements (or the forgery itself) intelligently by hiding the subtle artifacts thereby overcoming the forensic detectors [11]. This line of research has gained importance as it points out the flaws and loop holes in forensic algorithms leading to more robust techniques.

In this paper we concentrate on anti-forensics of CE images. Many techniques have been proposed to detect CE in images using first order statistics. For example, Stamm and Liu in [10] and [12] proposed to detect CE in images by leveraging the peak and gap artifacts created by CE operation on the histogram of the images. In [13], the authors estimate whether an image is contrast enhanced and reconstruct the original image. Other histogram based CE detectors involve [14] and [15].

A lot of anti-forensic strategies have been proposed against such first order statistics based CE detectors. For example, in [16], Cao et al implemented a local random dithering in the primary mapping of CE to avoid peaks and gaps in the histogram of the resulting enhanced image. Similarly, Kwok et al in [17] use Internal Bit Depth Increase method to increase the precision in avoiding peak and gap artifacts. Also, Barni et al in [11] proposed a universal anti-forensic technique to counter histogram based manipulation detectors. Comesana-Alfaro and Perez-Gonzalez in [18] propose a general attacking method using a single target function against histogram based detectors. Cao et al. in [19] propose trace forging and trace hiding attacks against CE detectors.

Since first order statistic based CE detection techniques are shown to be less robust by the above mentioned anti-forensic techniques [7], CE detectors based on other metrics were proposed. Authors in [20] used the inter channel dependency because of color image interpolation to detect CE. Similarly, a recent algorithm proposed by De Rosa et al in [7] looks at the Grey Level Co-occurrence Matrix (GLCM) of an image to determine whether it is enhanced or not. This uses second order statistics of the image and is shown to be effective against anti-forensic techniques targeted at histogram based detectors.

We propose an effective Anti-forensic Contrast Enhancement (ACE) technique using a variation of the Total Variation (TV) norm image restoration [21] technique. The algorithm performs contrast enhancement on an image by solving an optimization problem. The problem is formulated such that even though the solution looks contrast enhanced, it has lower Total Variation and characteristics similar to the original image. More importantly, we want the histogram and GLCM of the resulting image to be smooth like that of an un enhanced image's histogram and GLCM. This will degrade the performance of aforementioned first and second order statis-

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tics based detectors. We perform extensive experiments on a large database to evaluate the performance of the proposed technique against detectors [7] and [15].

The rest of the paper is organized as follows. Section II contains the proposed scheme of anti-forensic CE. Section III explains the effect of our algorithm on GLCM, histogram and image quality. Section IV details the dataset creation and defines the parameters used in the algorithm. Section V explains the experiments performed and the results obtained. Section VI concludes the paper.

II. Proposed Anti-Forensic Scheme

Let $\mathbf{X}$ be the original image of size $M \times N$that an adversary wants to enhance. CE operation is a pixel wise non linear mapping. Gamma Correction for example, can be given as

$$\mathbf{Y}_{m,n} = round\left(255\left(\frac{\mathbf{X}_{m,n}}{255}\right)^g\right) \tag{1}$$

where, g is the gamma value, $\mathbf{Y}_{m,n}$ is the element corresponding to $\mathbf{X}_{m,n}$ after GC and m and n are the pixel indices. We represent the Conventional CE (CCE) operation on an image as a function, i.e $\mathbf{Y} = \phi(\mathbf{X})$ where, $\phi(\cdot)$ is the element wise CE function. This function may be Gamma Correction (eq (1)) or Histogram Stretching[1]. The peaks and gaps in histogram or empty rows and columns in GLCM support the fact that the Total Variation (TV) of a CCE image is relatively high. Anisotropic TV of can be defined according to [21] as

$$\|\mathbf{X}\|_{ATV} = \sum_{m,n} |\mathbf{X}_{m+1,n} - \mathbf{X}_{m,n}| + |\mathbf{X}_{m,n+1} - \mathbf{X}_{m,n}| \tag{2}$$

where, $\|\cdot\|_{ATV}$ represents the Anistropic TV norm function as defined above. The matrix version of above equation can be written as $|\nabla_x \mathbf{X}| + |\nabla_y \mathbf{X}|$. The first [15] and second [7] order statistics based detectors utilize the large variation in the histogram and GLCM respectively of a CCE image to detect CE. Minimizing the total variation will minimize the gradient of an image which in turn will make the image smooth. Incorporating this idea, we propose an optimization formulation that will perform CE without introducing empty rows and columns in GLCM or peaks and gaps in histogram.

We are looking for an image $\mathbf{Y}$ that looks like $\phi(\mathbf{X})$, but has lower Total Variation. In addition, the image should be similar to the original image $\mathbf{X}$. This can be thought of as looking for a middle ground between the original image $\mathbf{X}$ and the CE image $\phi(\mathbf{X})$ with low TV. The optimization problem can now be formulated as

$$\min_{\mathbf{Y}} \frac{w_1}{2}\|\mathbf{Y}-\mathbf{X}\|_2^2+\frac{w_2}{2}\|\mathbf{Y}-\phi(\mathbf{X})\|_2^2+(|\nabla_x \mathbf{Y}|+|\nabla_y \mathbf{Y}|) \tag{3}$$

where w_1 and w_2 are regularization parameters whose values are determined experimentally and $\|\cdot\|_2^2$ represents the square of L2 norm function [21]. The first term is for getting an image with the characteristics of the original image. The second term in the above equation ensures that the solution is closer to the CE image, while the third term is the TV norm regularization term. We found out that minimizing the TV norm term smoothens the image too much. The first term

[1]Specific Gamma Correction and Histogram Stretching operations performed in the experiments are defined in Sec IV

Initialize: $\mathbf{Y}^0 = \mathbf{X}$, $d_x^0 = d_y^0 = b_x^0 = b_y^0 = 0$
while $\|\mathbf{Y}^k - \mathbf{Y}^{k-1}\|_2 > tol$ **do**
$\mathbf{Y}^{k+1} \rightarrow$ solve eq (7)
$d_x^{k+1} = shrink(\nabla_x \mathbf{Y}^{k+1} + b_x^k, \mu/\lambda)$
$d_y^{k+1} = shrink(\nabla_y \mathbf{Y}^{k+1} + b_y^k, \mu/\lambda)$
$b_x^{k+1} = b_x^k + (\nabla_x \mathbf{Y}^{k+1} - d_x^{k+1})$
$b_y^{k+1} = b_y^k + (\nabla_y \mathbf{Y}^{k+1} - d_y^{k+1})$
end while

Fig. 1. Algorithm to solve eq (4)

helps in ensuring that the resulting image is similar to that of the original image and is not extremely smooth or contrast enhanced. This increases the visual quality and efficiency of the solution for appropriate values of w_1 and w_2. We consider the problem defined in eq (3) as an integrated CE problem i.e. we perform CE by formulating it as an optimization problem rather than as a post processing problem [16]. This means that we know the CE function $\phi(\cdot)$ beforehand.

In order to solve eq (3) we resort to the Split Bregman [21] method. The optimization equation after introducing the necessary auxiliary variables becomes

$$\begin{aligned}\min_{\mathbf{Y},\mathbf{d_x},\mathbf{d_y}} & \frac{w_1}{2}\|\mathbf{Y}-\mathbf{X}\|_2^2 + \frac{w_2}{2}\|\mathbf{Y}-\phi(\mathbf{X})\|_2^2 + |d_x| \\ & + |d_y| \ + \frac{\lambda}{2}\|d_x - \nabla_x \mathbf{Y}\|_2^2 + \frac{\lambda}{2}\|d_y - \nabla_y \mathbf{Y}\|_2^2\end{aligned} \tag{4}$$

where $\nabla_x \mathbf{Y}$ and $\nabla_y \mathbf{Y}$ are replaced by auxillary variables d_x and d_y respectively [21] and λ is a regularization parameter that controls the amount of smoothing. The last two terms ensure that this replacement holds. Introducing the Bregman variables and following [21], the sub problems to solve in each iteration are given as

- $\mathbf{Y}$ sub problem

$$\begin{aligned}\mathbf{Y}^{k+1} = \min_{\mathbf{Y}} & \frac{w_1}{2}\|\mathbf{Y}-\mathbf{X}\|_2^2 + \frac{w_2}{2}\|\mathbf{Y}-\phi(\mathbf{X})\|_2^2 + \\ & \frac{\lambda}{2}\|d_x^k - \nabla_x \mathbf{Y} \ - b_x^k\|_2^2 + \frac{\lambda}{2}\|d_y^k - \nabla_y \mathbf{Y} \ - b_y^k\|_2^2\end{aligned} \tag{5}$$

- d sub problem

$$\begin{aligned}\{d_x^{k+1}, d_y^{k+1}\} = \min_{d_x,d_y} & |d_x| + |d_y| + \\ & \frac{\lambda}{2}\|d_x^k - \nabla_x \mathbf{Y} \ - b_x^k\|_2^2 + \frac{\lambda}{2}\|d_y^k - \nabla_y \mathbf{Y} \ - b_y^k\|_2^2\end{aligned} \tag{6}$$

Where b_x and b_y are the bregman variables [21] and k is the present iteration. The optimality condition for the $\mathbf{Y}$ sub problem in eq (5) is given as

$$\begin{aligned}((w_1 + w_2)\mathbf{I} - \lambda\Delta)\mathbf{Y}^{k+1} &= w_1\mathbf{X} + w_2\phi(\mathbf{X}) \\ &+ \lambda\nabla_x^T(d_x^k - b_x^k) + \lambda\nabla_y^T(d_y^k - b_y^k)\end{aligned} \tag{7}$$

where $\mathbf{I}$ is the Identity matrix and Δ is $(\nabla_x^T\nabla_x + \nabla_y^T\nabla_y)$. The above equation can be solved using conjugated gradient descent or Gauss-Seidel method [21]. The d sub problem in eq (6) can be solved by soft thresholding [21]. The entire algorithm to solve eq (4) is given in Fig 1. The solution to

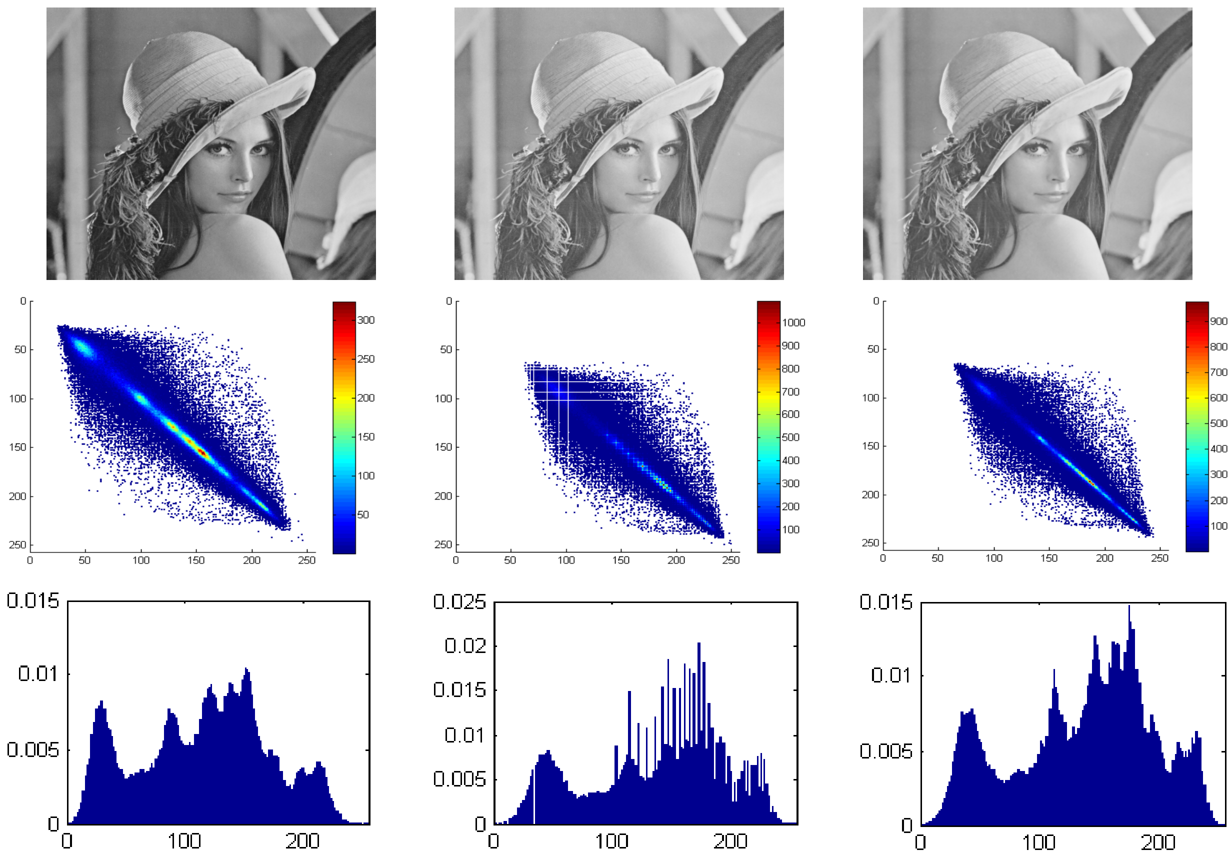

Fig. 2. The first row from left to right contains the original, CCE and ACE (CE here is Gamma Correction with g 0.6) images. The second row gives their corresponding GLCM (x and y-axes give gray values and colorbar gives the number of co-occurence). The third row shows the corresponding normalized gray value histograms (x-axis is Gray value and y-axis is the probability of occurence) of the images.

this algorithm gives the Anti-forensically Contrast Enhanced (ACE) image. The effects of the anti-forensic operation on GLCM and histogram are discussed in the next section.

III. Effect on Histogram and GLCM

The technique discussed in Section II gives us the final anti-forensically contrast enhanced image. In order to be able to degrade the performance of CE detector proposed in [7] we need to analyze the GLCM of the resulting image and compare it with the original. The GLCM of 512×512 gray scale Lena image (original), its gamma corrected version (CCE for Conventional CE) with gamma 0.6 and the Anti-forensically gamma corrected (ACE for Anti-forensically Contrast Enhanced) version are given in the second row of Fig 2. It can be clearly seen that the empty rows and columns introduced in the CCE version is filled by the anti-forensic operation resulting in a GLCM which is quite similar to that of the original. Also, the corresponding images from which the GLCMs were obtained are given in the first row. It can be seen that the ACE image is very similar to the CCE image with a high PSNR of 38.76dB between them.

Third row in Fig 2 shows the gray level normalized histograms of the original, CCE and ACE images. It can be clearly seen that the histogram of the ACE image looks very much similar to that of the original. i.e. peaks and gaps seen in the histogram of CCE image are not there anymore. This shows that the algorithm can degrade the performance of first order statistics based CE detectors such as [15]. The proposed algorithm performs CE on an image without introducing peaks and gaps in its histogram or empty rows and columns in its GLCM. The efficiency of the technique in undermining the CE detectors is detailed in the following sections.

IV. Dataset and Parameters

In order to evaluate the anti-forensic effectiveness of the proposed algorithm quantitatively, we perform experiments to test the CE detectors [7] and [15] on images enhanced using the proposed algorithm. For this, we take 5000 random images of size 512×512, from the 10000 PNG images in the BOSS [22] database. Let this be the 'original dataset'. We then create 'CCEGC' (Conventional CE using Gamma Correction) dataset by performing GC on the 5000 'original' images with g in eq (1) chosen randomly from the set $\{0.6, 0.8, 1.2, 1.4\}$. Similarly an 'ACEGC' (Anti-forensic CE Gamma Correction) dataset is created by performing GC using the proposed algorithm with the same g. We also generate similar 'CCEHS' (Conventional CE Histogram Stretching) and 'ACEHS' (Anti-forensic CE Histogram Stretching) datasets by performing Histogram Stretching CE normally and using proposed technique respectively. The HS operation maps pixel values such that 1% of data is saturated at value 0 and 1% is saturated at 255.

Values for the regularization parameters used in the algorithm are chosen experimentally to get high quality resulting image and high efficiency against the CE detectors. Accordingly, λ in eq (5) is chosen as 0.05 and μ in the d sub problem as given in Fig 1 is set as 3. The weight parameters w_1 and w_2 determine how close the image is to original and CE respectively. Hence, these are chosen differently based on the enhancement performed. For example, GC for gamma value above 1, i.e. darkening the image, they are chosen to be 0.4 and 1.2 respectively. For gamma value below 1, 0.1 and 1.5 and for Histogram Stretching operation 0.2 and 1.4 respectively are chosen. This dynamic weighting is based on heuristics and experiments to give the best results.

V. Experimental Results

First we discuss the experiments performed to evaluate the CE detector proposed in [7]. We extract the second order features using their algorithm from all the 25000 images from all the datasets. We recreate the validation in [7] by training images from 'original' and 'CCEGC' datasets. Testing on the remaining data from these datasets give the accuracy of the CE detector. To see if this trained model can detect CE in images from the 'ACEGC' dataset, we include these images in the testing data instead of 'CCEGC'. The ROC curve[2] for detection for original Vs CCEGC images and original Vs ACEGC images are given in Fig 3. It can be seen that the True Positive Rate (TPR) for a False Positive Rate (FPR) of 0.1 drops from 0.8 to 0.18. We perform similar set of experiments using 'CCEHS' and 'ACEHS' datasets. The ROC curve for this detection is given in Fig 3. It is observed that TPR for an FPR of 0.1 drops from 0.85 to 0.25. It is very clear that the CE detector fails to detect CE when enhancement is performed using the proposed technique. The accuracy[3] in detection of GC and HS for CCE and ACE datasets vs the original dataset, separately for different percentage of training set (as done in [7]) is given in Table I. TPR gives the percentage of CE images classified correctly as CE and TNR gives the percentage of original images classified correctly as original.

TABLE I
Detection accuracy (percentage of images classified correctly in each class) of CE detector in [7] for original Vs CCE and original Vs proposed ACE

Experiment →		Gamma Correction			Histogram Stretching		
Training set size →		25%	50%	75%	25%	50%	75%
Original Vs CCE	TPR	87.5%	88%	89%	88%	89%	89%
	TNR	82.7%	89%	91%	86.3%	89%	91%
Original Vs proposed ACE	TPR	**33%**	**33%**	**29%**	**55%**	**51%**	**45%**
	TNR	87%	88.2%	90%	84%	87%	91%

Similarly, owing to the observation in the histograms in Fig 2, we implement the CE detector in [15] which is based on first order statistics on images enhanced using our method. The threshold for the number of bins as described in [15] is set to zero and is tested on the datasets created in Section IV. The percentage of images classified correctly in each class for both GC and HS enhancements is given in Table II. It is clear from the table that the first order statistic based CE detector also fails to detect CE in images enhanced using the proposed technique. The average PSNR between 'CCEGC' images and 'ACEGC' images is 38dB (99% of images give above 30dB) and between 'CCEHS' images and 'ACEHS' is 36dB (84% of images give above 30dB). This shows that the proposed technique makes the resulting image look contrast enhanced. Also the algorithm takes approximately 2 seconds to create an ACE image of size 512×512 using MATLAB in a computer with processing speed of 2.2 GHz and memory of 8GB RAM.

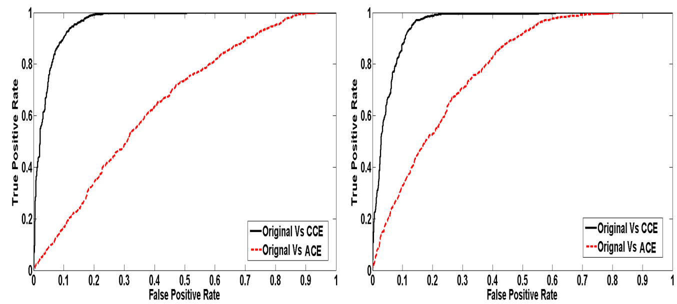

Fig. 3. ROC curve for detection of CE for original Vs CCE and original Vs ACE using CE detector proposed in [7] for Gamma Correction (left) and Histogram Stretching (right)

TABLE II
Detection accuracy (percentage of images classified correctly in each class) of CE detector in [15] for original Vs CCE and original Vs proposed ACE

Experiment	Original Vs CCE		Original Vs proposed ACE	
	TPR	TNR	TPR	TNR
Gamma Correction	96%	100%	**0.3%**	100%
Histogram Stretching	95.48%	99%	**0.1%**	99%

VI. Conclusion

We propose an effective Anti-forensic Contrast Enhancement (ACE) technique using TV norm optimization that performs efficiently against both first order [15] and second order [7] based CE detectors. The resulting image's visual quality is high as indicated by the PSNR values in experimental section. The efficiency of the approach in degrading the performance of the second order CE detector [7] is very high. The TPR of identifying CE as CE drops from 90% to 29% in case of GC and 91% to 45% in case of HS as in Table I. With respect to the first order statistic based detector of [15], the TPR of identifying CE as CE drops from 96% to a mere 0.3% in case of GC and 96% to 0.1% in case of HS as given in Table II. The results thus call for more efficient CE detectors that are robust against anti-forensic approaches.

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[2]All experiments are done using RBF kernel SVM [23] and ROC curves are plotted after a grid search of C and gamma values to get those that gave the best average accuracy over five trials using different set of training and testing sets.

[3]All the above experiments are also performed on the standard uncompressed UCID database [24] by taking 500 images randomly from the entire dataset (as in [7]). It is to be noted that the results were very similar to that obtained using BOSS database and not given here owing to space constraints.

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