DETECTION OF IMAGE SHARPENING BASED ON HISTOGRAM ABERRATION AND RINGING ARTIFACTS

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ABSTRACT

With the wide use of sophisticated photo manipulation, capability of digital images for recording authentic scene information has been addressed with public suspicion. So it is urgent to develop forensics techniques for verifying photographs' originality and authenticity. In this paper, a blind forensic algorithm is proposed to detect sharpening manipulation in digital images. Gradient aberration of the gray histogram generated from unsaturated luminance regions of an image, is measured and employed to capture trails of sharpening operation. Ringing artifacts around step edges are exploited to provide another complementary clue, especially useful when the histogram-based features are not available. Tests on plenty of photo images show the effect-tiveness of our proposed sharpening detection scheme.

***Index Terms*—** Image forensics, sharpening detection, histogram aberration, ringing artifacts

1. INTRODUCTION

As digital technique advances, plenty of powerful media editing softwares have made it possible to create sophisticated photo forgeries. Seeing from digital images is no longer believing. It is necessary to develop authentication techniques to verify their originality and integrity. Existing methods including watermarking and digital signature belong to active image authentication techniques. Their applications in practice are limited because some preprocessing such as watermark embedding and signature generation must have been done before the images' distribution. As a result, there is an increasing need for developing blind forensics methods to detect image alterations, without any extrinsic signature.

In general, all image manipulations can be classified into content-changing and noncontent-changing operations [1]. Correspondingly, digital image forensics methods can be categorized into *hard forensics* and *soft forensics*, which aim to identify the noncontent-changing and content-changing operation history respectively. Hard forensics is much useful in military security and law forensics fields, where even the common image manipulations such as image sharpening and compression are not permitted. In this paper, we focus on the hard forensics of image sharpening operation. While sharpening of an image does not necessarily prove malicious tampering, its presence destroys the image's originality.

To detect whether an image has undergone any form of alteration, the use of various operations must be examined. Previous work of tamper detection concentrates on the detection of blurring [2], resampling [3], image splicing [4], and double compression [5] and so on. Recently, a blind forensics algorithm for detecting contrast enhancement in digital images has been proposed in [6]. Although gamma transformation and histogram equalization can be detected successfully by this scheme, sharpening operation escapes its detection. Because peaks and gaps are not incurred in the gray histogram of a sharpened image. To the best of our knowledge, there is no prior work addressing the problem of blind image sharpening detection.

In this work, both global statistic metric and local edge analysis are exploited to capture the inconsistency caused by sharpening operation. Gradient aberration on the two sides of a calibrated histogram affords the first clue for sharpening detection. Ringing artifacts around step edges are used as a second fingerprint. In the following, the sharpen-ing detection scheme is presented specifically. Performance evaluations over an elaborated data set will be shown, followed by discussions of remaining challenges.

2. PROPOSED SHARPENING DETECTION SCHEME

Checking the artifacts uniquely caused by sharpening operation is the basic motivation of this work. To find out such manipulation signatures, two kinds of metric are explored from statistics and signal-processing aspects respectively. They are the gradient on each end of a gray histogram and the ripple amplitude of ringing artifacts around step edges. Any aberration and inconsistency of such features on the whole image are regarded as evidence for sharpening affirmation. After extraction, these features are fed into a fisher linear classifier, which acts as a judger and makes a decision: the test image has been sharpened or not. An overview of the proposed scheme is given in Fig.1. For unsaturated images, which have narrow histograms, the histogram-sides gradient features can’t be gained due to none pixels falling on the marginal ranges of the gray histogram. In such scenarios, features extracted based on ringing artifacts would act as a powerful substitute and complete the task of sharpening detection cooperatively.

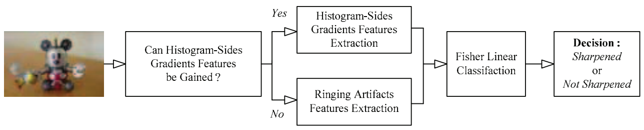

Fig. 1. A system for automatic image sharpening detection

2.1. Histogram Gradient Metric

Most of the commonly used digital images belong to limited dynamic range image data, which are fit for showing on most display devices. The scene irradiance can only be recorded at coarse levels on photographs. Such a character makes the graylevel histogram of a natural image keep smooth, and usually have two monotonically descend-ing tails. Along the direction towards histogram’s center, histogram gradient is positive on two ends. Such positive gradient features will be destroyed by sharpening operation.

In an unsaturated image, the near-black and near-white pixels often fall into edge and texture regions sparsely, where high frequency components are quite abundant. However, the inherence of sharpening manipulation is to add high-pass filtered components to original signal. If an image’s gray histogram is not too narrow, near-black and near-white pixels in its sharpened copies will become blacker and whiter respectively, till turning into pure black and pure white. At this time a local maximum appears at each border bin, namely the bins with sequence number 0 and 255 for 8-bit grayscale images. Along the center-ward direction, histogram decreases monotonically on two ends and possesses negative gradient features, which are opposite from that of unsharpened images. In fact, the discussed gradient attribute can be measured only if the unsaturated image’s histogram covers adequate graylevels and is not too narrow. If not, it has to be sent to another sharpening detector based on ringing artifacts.

With regard to high and low end saturated images, the histograms present negative gradient characteristics even if they have not been sharpened. To capture the gradient discrepancy, a corrected histogram is computed on regions where blocky white (255) and black (0) pixel regions are removed. Such a calibrated histogram can generate similar gradient features as those of end unsaturated images.

For the purposes of this work, we consider 8-bit grayscale images, where a color image can be seen as three separate grayscale ones. An image histogram *h(x)* is calcul-ated on regions without blocky white and black pixel areas. The desired gradient features are designed as follows.

$$\begin{cases} f_0 = \frac{1}{\mathrm{T}}\int_0^T \frac{\partial h(x)}{\partial x}dx & if \ \sum_{x=0}^{\alpha\cdot\mathrm{T}} h(x) > 0 \\ f_{255} = \frac{1}{\mathrm{T}}\int_{255-T}^{255}\left(-\frac{\partial h(x)}{\partial x}\right)dx & if \ \sum_{x=255-\alpha\cdot\mathrm{T}}^{255} h(x) > 0 \end{cases} \tag{1}$$

Here T determines the range for calculating histogram gradient. α is a factor used to detect whether a histogram covers sufficient graylevels and the gradient features can be constructed. Once being extracted, such features are to be fed into a fisher linear classifier.

2.2. Ringing Artifacts Analysis

To estimate the sharpening operation history of images whose histogram gradient features are absent, another sharpening detection method based on ringing artifacts analysis is proposed collaboratively in this subsection. Through analyzing the sharpening process performed to step edges in a digital image, amplitude vibration is proved to be present around edge vicinities. Presence of such a phenomenon is directly used as fingerprint for sharpening identification, refered as ‘ringing artifacts’.

2.2.1. Modeling sharpened step edges

Edges are the most important structural components in an image. A step edge is one kind of the most familiar edges, which can be modeled by an ideal step signal,

$$u(x) = \begin{cases} A+B \ , & x \geq 0 \\ B \ , & x < 0 \end{cases} \quad x \in \mathrm{Z} \tag{2}$$

where A and B denote edge height and one-side amplitude respectively, as shown in Fig.2. And x is the local position coordinates crossing the step edge rims.

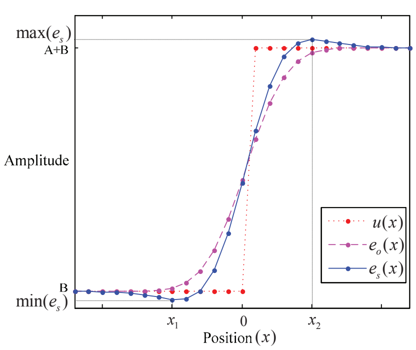

Fig. 2. Signal model for three kinds of step edge. $u(x)$: the ideal step edge; $e_o(x)$: the natural step edge in unsharpened images; $e_s(x)$: the sharpened step edge in sharpened images.

Because of the lowpass impact of imaging pipeline, a step edge in original photographs can be simulated as the convolution between $u(x)$ and a normalized Gaussian lowpass filter $g(x,\sigma)$ [7]. That is,

$$e_o(x) = u(x)\otimes g(x,\sigma)$$
$$= \begin{cases} \frac{A}{2}(1+\sum_{n=-x}^{x} g(n,\sigma)) + B \ , \quad x \ge 0 \\ \frac{A}{2}(1-\sum_{n=x+1}^{-x-1} g(n,\sigma)) + B \ , \quad x < 0 \end{cases} \tag{3}$$

Based on such prior knowledge, the sharpen operation itself can be represented as formula (4) by introducing a sharpening filter $h_{sharp}(x,\sigma_s)$, which is a highpass filter.

$$e_s(x) = e_o(x) + \lambda\, e_o(x) \otimes h_{sharp}(x,\sigma_s)$$
$$= \begin{cases} \frac{A}{2}(1+\sum_{n=-x}^{x}((1+\lambda)g(n,\sigma)-\lambda g(n,\sqrt{\sigma^2+\sigma_s^{2}})))+B, \ x\in \overline{Z^-} \\ \frac{A}{2}(1-\sum_{n=x+1}^{-x-1}((1+\lambda)g(n,\sigma)-\lambda g(n,\sqrt{\sigma^2+\sigma_s^{2}})))+B, \ x\in Z^- \end{cases} \tag{4}$$

where λ is the strength factor of sharpening operation, and

$$h_{sharp}(x,\sigma_s) = \delta(x) - \frac{1}{\sqrt{2\pi}\sigma_s}\exp(-\frac{x^2}{2\sigma_s^{\ 2}}) \ , \ x \in \mathrm{Z} \tag{5}$$

2.2.2. Measure of ringing artifacts

Firstly, we define an observation variable as follows,

$$R(e_*) = \frac{\left|(\max(e_*)-\min(e_*))\right| - A}{2} \tag{6}$$

where e_* can be considered as e_o or e_s. Specifically,

(1) If $e_* = e_o$, it refers to step edges in unsharpened images. Combining with formula (3), a conclusion can be easily made. That is,

$$R(e_o) \equiv 0 \tag{7}$$

(2) If $e_* = e_s$, it refers to step edges in sharpened images. The maximum and minimum of sharpened step signal can be computed using the differential method. Then the observed variable can be rewritten as

$$R(e_s) = A\sum_{n=x_2+1}^{+\infty}(\lambda g(n,\sqrt{\sigma^2+\sigma_s^{\ 2}}) - (1+\lambda)g(n,\sigma)) \tag{8}$$

We can see that $R(e_s)$ is determined by four parameters: $\lambda, \sigma, \sigma_s$ and A. Their relationship graph is shown in Fig.3.

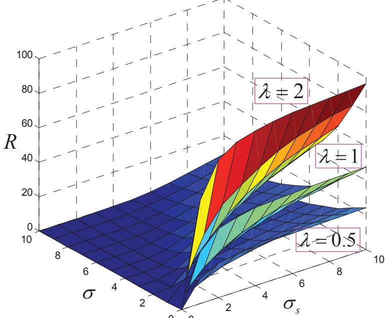

Fig. 3. The relationship graph $R(e_s) \sim (\lambda,\sigma,\sigma_s)$, $A=100$

Here A is fixed as a constant. It is apparent that $R(e_s)$ always keeps positive, which differs from the case of $e_* = e_o$.

Based on the above discussion, we can make a conclusion that the variable defined in formula (6) can be exploited to identify sharpening operations. Such a metric is regarded as the measure of ringing artifacts and to be served as features sent into a Fisher linear classifier, which distinguishes sharpened images from unsharpened ones. This detector acts as a second-step filter and work collaboratively with the first-step detector.

3. EXPERIMENTS AND DISCUSSIONS

3.1. Data Sets

Both original unsharpened images and sharpened ones are to be prepared for evaluating our proposed sharpening detection algorithm. The original image set consists of 403 photo images captured by several different digital cameras. All of them are saved as JPEG format with different quality factors. We made best efforts to ensure the variety of contents and illumination environments. Subjects of these images range from nature landscapes to human activities. Correspondingly, sharpened samples (denoted by I_s) of the original images (denoted by I_o) are simulated as

$$I_s(x,y) = I_o(x,y) + \lambda\, \mathrm{I}_o(x,y) \otimes g(x,y,\sigma_s) \tag{9}$$

where $g(x,y,\sigma_s)$ is a normalized Gaussian lowpass filter with kernel radius $\sigma_s = 0.7$. And λ is the amount of high-frequency contribution, which is selected from the set $\{0.4, \ 0.7, \ 1.0\}$ to simulate sharpening operations with different strength.

3.2. Simulation Results and Discussions

To assess the performance of the sharpening detector, we perform two-class classification experiments to identify whether a test image has been sharpened or not. Original and sharpened images are taken as positive and negative samples respectively. *TP* is determined by calculating the percent of correctly classified sharpened images and *FP* is the percent of misclassified original ones. *Precision* means the rate of correctly classified for all samples.

The sharpening detection results are shown in Table 1. We can see that most samples have obtained histogram-based features, in the worst scenarios that only 22 of the 403 original images can not get them. Such a result proves that histogram-based detection technique is quite effective, and can be used on most images. The ringing-based detector also performs well, despite its higher computation complexity. Fortunately, there does not leave too many samples to be processed by it.

Table. 1. Precision of image sharpening detection under different sharpening strength, when FP=0.1 / 0.2. 'P+N' denotes the number of sharpened plus unsharpened samples.

Precision (P + N)		histogram tech.	ringing tech.	joint
λ	0.4	0.871 / 0.832 (387+381)	0.553 / 0.526 (16+22)	0.856 / 0.818 (403+403)
	0.7	0.939 / 0.891 (401+381)	0.792 / 0.792 (2+22)	0.934 / 0.888 (403+403)
	1.0	0.941 / 0.897 (403+381)	0.864 / 0.773 (0+22)	0.939 / 0.894 (403+403)

Detection performance under different sharpening strength (λ) is also tested. Weaker sharpening operation is apt to make the detection become harder. Such as in the scenarios $\lambda = 0.4$, none obvious visible difference between original and sharpened images can be found out by human vision. The induced ringing artifacts are so feeble that our ringing-based technique fails. However, the last *Precision* can arrive at 0.856 while $FP = 0.1$ all the same.

Detailed result of the detection based on histogram-based features is shown in Fig. 4. It behaves perfectly. To verify the effectiveness of ringing-based features, we extract them from the whole 806 samples and send to a fisher classifier. The gained precision is kept above 0.60 if $\lambda = 0.7$ or $\lambda = 1.0$, while descends to 0.55 when $\lambda = 0.4$. Such results prove that ringing-based sharpening detector is also effective, which can serve as a powerful complement for the histogram-based technique.

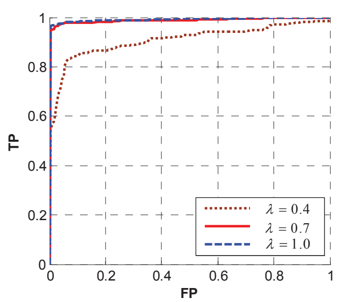

Fig. 4. The ROC curves for the classification of sharpened and unsharpened images by histogram technique, under the conditions of different sharpening strength.

Capability to resist double JPEG compression of our algorithm is also tested. In practice, saving as new JPEG images is operated frequently after sharpening operation. Test results are demonstrated in Table 2. Although double compression decreases precision to some extent, acceptable performance can still be achieved. In fact, the second JPEG compression disturbs the sharpening recognition ability of histogram features seriously. However, the ringing-based features are proved to be robust enough to resist double compression. Cooperative working of them will be able to detect sharpening operation accurately. Besides, high reliability and security of the proposed algorithm can be ensured if test images have not been double compressed.

The sharpening detection scheme can work collaboratively with the contrast enhancement detection method proposed in [6], which can't discover any fingerprint left by sharpening operation and fails to detect its existence.

Table. 2. Precision of image sharpening detection under post JPEG compression with different Q, when FP=0.1 / 0.2.

Precision (P + N)		histogram tech.	ringing tech.	joint
Q	70	0.699 / 0.715 (401+387)	0.778 / 0.667 (2+16)	0.700 / 0.715 (403+403)
	80	0.683 / 0.711 (400+384)	0.773 / 0.727 (3+19)	0.685 / 0.712 (403+403)
	90	0.700 / 0.719 (401+386)	0.750 / 0.700 (3+17)	0.701 / 0.719 (403+403)

4. CONCLUSION

In this paper, we present the sharpened image detection problem firstly in digital image forensics research field. An image sharpening detection algorithm is designed based on histogram gradient aberration and ringing artifacts metric. Experiment results show that our approach is effective for detecting sharpening manipulation. We also discussed the issues of robustness and practical applications.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

[1] W. Feng and Z.-Q. Liu, "Region-Level Image Authentication Using Bayesian Structural Content Abstraction," *IEEE Trans. on Image Processing*, vol. 17, no. 12, pp. 2413–2424, 2008.

[2] D. Hsiao and S. Pei, "Detecting Digital Tampering by Blur Estimation," *1st International Workshop on Systematic Approaches to Digital Forensic Engineering*, Washington, 2005.

[3] A. C. Popescu and H. Farid, "Exposing Digital Forgeries by Detecting Traces of Re-sampling," *IEEE Transactions on Signal Processing*, vol. 53, no. 2, pp.758-767, 2005.

[4] Y.-F. Hsu and S.-F. Chang, "Image Splicing Detection Using Camera Response Function Consistency and Automatic Segmentation," in *International Conference on Multimedia and Expo*, Beijing, 2007.

[5] J. Lukas and J. Fridrich, "Estimation of Primary Quantization Matrix in Double Compressed JPEG Images," in *Digital Forensic Research Workshop*, Cleveland, Ohio, 2003.

[6] M. Stamm and K. J. R. Liu, "Blind Forensics of Contrast Enhancement in Digital Images," in *International Conference Proceedings on Image Processing*, San Diego, 2008.

[7] H. Hu and G.de Haan, "Low Cost Robust Blur Estimator," in *International Conference Proceedings on Image Processing*, Atlanta, GA, 2006.