Forensic detection of noise addition in digital images

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Abstract. We proposed a technique to detect the global addition of noise to a digital image. As an anti-forensics tool, noise addition is typically used to disguise the visual traces of image tampering or to remove the statistical artifacts left behind by other operations. As such, the blind detection of noise addition has become imperative as well as beneficial to authenticate the image content and recover the image processing history, which is the goal of general forensics techniques. Specifically, the special image blocks, including constant and strip ones, are used to construct the features for identifying noise addition manipulation. The influence of noiseing on blockwise pixel value distribution is formulated and analyzed formally. The methodology of detectability recognition followed by binary decision is proposed to ensure the applicability and reliability of noiseing detection. Extensive experimental results demonstrate the efficacy of our proposed noising detector.

Keywords: information security; image analysis; image authentication; digital forensics; noise addition.

Paper 13461 received Aug. 17, 2013; revised manuscript received Jan. 17, 2014; accepted for publication Feb. 11, 2014; published online Mar. 12, 2014.

1 Introduction

With the development of multimedia editing techniques, digital image manipulation has become rather easy and convenient. In the meantime, digital images are also easily tampered by malicious users at a low cost. Such practical situations result in the flooding of forged photographs in the current digital world. The scene and content seen from a digital image may become no longer believable. The emergence of unauthentic media destroys the security and credibility of multimedia information. To verify the integrity and authenticity of images, digital image forensics techniques have been presented in a blind and passive manner.

In previous works, plenty of algorithms have been proposed to detect the following two kinds of digital image alterations: (1) noncontent-changing manipulations such as resampling, JPEG compression, sharpening, median filtering (MF), and contrast enhancement; and (2) content-changing manipulations, i.e., image splicing.

Recently, as a common manipulation, noise addition has attracted many interests in the digital forensics community. For assisting image tampering, noise may be intentionally and locally added to conceal tampered regions or create special visual effects. As such, the regional noise levels in spliced images are inconsistent. In Ref. 17, the local addition of noise to specific image regions is detected by checking the fluctuations in locally estimated signal-to-noise ratios. In Refs. 18 and 19, the noise statistics, i.e., variance, are estimated at each image block to locate suspicious regions. In Ref. 20, consistency of the noise-level functions estimated at different regions is checked to identify forged videos. However, such methods become invalidated if noise is globally added to an image or a video frame, since the localized noise variations are not incurred. In Ref. 21, the noise addition in image patches is detected by a fusion procedure in conjunction with derivative correlation features. However, the specific manipulation type, i.e., noise addition, fails to be identified uniquely by such a general manipulation detection method. In Ref. 12, a technique is proposed to detect the global addition of noise to an image that has previously suffered JPEG compression. Such a technique works by applying a predefined mapping with known fingerprint to pixel values. The mapping is designed such that an identifying feature of its fingerprint will be absent if noise was added. Although the method succeeds in detecting noise addition in the previously JPEG-compressed images, it invalidates in uncompressed images.

In this article, we propose a new algorithm to detect the global addition of noise in digital images, which can be either previously JPEG compressed or uncompressed. The novel detectable mechanism is designed to pick out the samples which are permitted to enter the formal noise addition—detection procedure. The image blocks with determinate pixel arrangement, which carry the manipulation trace of noise addition, are investigated detailely. The quantity of detected special blocks is used as the identifying feature, which is feed into a thresholding classifier to determine if noise addition occurred.

It should be pointed out that the detection of global noise addition is also significant. The global addition of noise may seem to be innocuous, except that the image quality degrades slightly. However, it is often used to disguise tampering traces or to remove the statistical artifacts left behind by other alterations. The successful detection of global noise addition can help to verify photograph images’ originality and to discover their processing history.

The rest of this article is organized as follows. In Sec. 2, the special blocks occurring in JPEG images are formulated formally, and the influence of noise addition on such special blocks is analyzed statistically. In Sec. 3, a scheme is proposed to detect the global noise addition in both previously...
JPEG-compressed images and uncompressed images. The evaluation results and discussions are presented in Sec. 4. Last, the conclusions are drawn in Sec. 5.

2 Noise Analysis in Special Blocks

In this section, the existence of special blocks in JPEG images and uncompressed images is first investigated. Then, the special blocks’ statistical changes incurred by noise addition are analyzed formally.

2.1 Special Blocks in Digital Images

The 8 × 8 special blocks, including the constant and the strip blocks, are widespread in JPEG images. Below, the principle behind the generation of such blocks is analyzed detailedly.

Generally, JPEG compression of an 8-bit grayscale image includes the steps of pixel value shift from [0, 255] to [−128, 127], blocks division, block discrete cosine transform (DCT), quantization, and entropy encoding. In each natural image, more or less flat regions exist. After applying DCT to a flat block, only direct current (DC) coefficient is large while alternating current (AC) coefficients are rather small. After quantization, it is reasonable to assume that there exist image blocks with sparse AC coefficients. Let the dequantized block DCT coefficients be denoted by \( F_{u,v} \), where \( u, v = 0, 1, \ldots, 7 \). The following two cases are investigated specifically.

Case 1. \( F_{u,v} = 0, (u,v) \neq (0,0) \). It refers that all AC coefficients are zeros. According to the definition of inverse DCT, the 8 × 8 constant block which has the same gray level for each involved pixel would occur in the decompressed image. That is

\[
f_{x,y} = \text{round}\left(\frac{1}{8}F_{0,0} + 128\right)
\]

where \( x, y = 0, 1, \ldots, 7 \) denote the local pixel coordinates, and \( \text{round}(\cdot) \) is the rounding operator. In the example, JPEG image is shown in Fig. 1(a), and a constant block is illustrated in Fig. 1(b).

Case 2. \( \sum_{v=1}^{7} |F_{0,v}| \neq 0 \) and \( F_{u,v} = 0, u, v = 1, 2, \ldots, 7 \). It refers that nonzero AC coefficients exist in the first row, while AC coefficients in other positions are zeros. As such, the strip block would be generated as

\[
f_{x,y} = \text{round}\left(\frac{1}{8}F_{0,0} + \frac{\sqrt{2}}{8} \sum_{v=1}^{7} F_{0,v} \cos\left(\frac{2\pi}{16} v\right) + 128\right)
\]

A strip block generated by such regularity is indicated in Fig. 1(c). We could see that the pixel gray levels in each column are determined by the coordinate \( y \), but keep invariant with \( x \).

According to the same principle, the strip block can also be generated if \( \sum_{u=1}^{7} |F_{u,0}| \neq 0 \) and \( F_{u,v} = 0, u, v = 1, 2, \ldots, 7 \). It refers that nonzero AC coefficients merely exist in the first column. The strip block in such a scenario is shown in Fig. 1(d). The pixel gray levels in each row are determined by \( x \) and invariant with \( y \).

Note that the constant block is also widespread in uncompressed images, where the purely flat regions such as sky and monochromatic surface often exist. Since the pixels in such flat regions have the same gray level, the 8 × 8 constant blocks occur connectively.

Fig. 1 Special blocks in a JPEG image. (a) The example image, (b) constant and (c and d) strip blocks.
2.2 Noise Analysis

In order to detect the manipulation of noise addition, the effect of noising on image pixels should be investigated in detail. After noising, the statistical probability that the pixel values in an $8 \times 8$ block keep invariant is deduced as follows.

In this work, we focus on the detection of noise in the form of independent and identically distributed (i.i.d.) for each pixel. Without the loss of generality, the common additive Gaussian noise is considered. Let the image block before and after noising be denoted by $f_{x,y}$ and $f'_{x,y}$, $x, y = 0, 1, \ldots, 7$, respectively. The random noise variable added to each pixel is denoted by $n_{x,y} \sim N (0, \sigma)$, where $\sigma$ denotes the standard deviation of Gaussian noise. We have

$$f'_{x,y} = \text{round}(f_{x,y} + n_{x,y}).$$

(3)

It is easy to find that $f_{x,y} + n_{x,y} \sim N(f_{x,y}, \sigma)$. As such, the probability that a pixel keeps invariant after noising, $P(f'_{x,y} = f_{x,y})$, can be computed as

$$P(f'_{x,y} = f_{x,y}) = P(-0.5 \leq n_{x,y} < 0.5).$$

(4)

Since the noise added to each pixel is i.i.d., the probability that an image block keeps invariant after noising, $P(f' = f)$, can be computed as

$$P(f' = f) = \prod_{x=0}^{7} \prod_{y=0}^{7} P(f'_{x,y} = f_{x,y})$$

$$= \left( \int_{-0.5}^{0.5} \frac{1}{\sqrt{2\pi\sigma}} \exp \left( -\frac{t^2}{2\sigma^2} \right) dt \right)^{64}.$$  

(5)

The relationship between such a probability and standard deviation $\sigma$ is illustrated in Fig. 2. It shows that the probability $P(f' = f)$ decreases with $\sigma$ and keeps lower than $10^{-6}$ even for $\sigma = 0.4$. Investigations show that the range $\sigma = 0.5$ to 2 is typically used in anti-forensics applications for removing other operations’ trace while preserving the image quality at an acceptable level. Without the loss of generality, we focus on the detection of noising in such range in this work. As such, any block even for the special ones would be altered after noise addition. The constant and strip blocks, respectively defined in Eqs. (1) and (2), will disappear in the noised image. As a result, noise addition can be identified by detecting the absence of special blocks.

3 Proposed Noise Detection Algorithm

In this section, a novel algorithm is proposed to detect the global noise addition in digital images. As shown in Fig. 3, the algorithm consists of two integrated parts: detectability recognition and noising detection. The latter part performs a binary classification by thresholding the number of special blocks within an image. If special blocks are absent, the noise addition is detected; else not. It is easy to conceive that the noise addition may be falsely detected in textured images. To overcome such deficiency, the detectability recognition procedure is designed to prefilter the highly textured images, which are primarily without special blocks.

3.1 Recognition of Detectable Images

The proposed noising detection technique mainly relies on the differentiation between special blocks and their noised versions. As a result, only the images containing such form of blocks would be considered for further detection. Here, the images with unaltered or noisy special blocks are referred as detectable image samples, which satisfy blockwise sparsity to a certain extent.

Generally, not a few pixels in the noised special blocks still own the primary gray levels due to the limited dithering and subsequent rounding operation. As such, the pixel gray level arrangement in both unnoised and noised special blocks has a certain sparsity. The detectable images are deemed to contain quantitative sparse blocks. Based on such considerations, the detectable image samples are recognized as in Algorithm 1.

It should be mentioned that the detectability recognition could avoid the possible misclassification on highly textured images, which typically own rather low sparsity measurement $S$. The fine-textured pixel regions such as grassland and flax might be regarded as noised ones.

3.2 Noising Detection

It can be noted that the special blocks typically exist in unnoised images. Specifically, the constant blocks occur concentratively in the smooth image regions of both uncompressed or JPEG images, whereas the strip blocks occur in
Algorithm 1 Detectability recognition.

**Step 1.** Divide the input 8-bit grayscale image $I$ into $8 \times 8$ blocks, denoted by $f_i$, $i = 1, 2, \ldots, M$, where $M$ is the total number of divided blocks.

**Step 2.** Calculate the gray-level histogram of each block, denoted by $H(i, k)$, $k = 0, 1, \ldots, 255$.

**Step 3.** Compute the blockwise sparsity as $S = \max_{0 \leq i < M} H(i, k)$, where $\max \{ \cdot \}$ means to compute the maximum value in an array.

**Step 4.** Measure the sparsity of the global image as $S = \text{med}(|S|)$. Here, $\text{med} \{ \cdot \}$ means to compute the median value in an array. $S_g$ denotes a set which consists of the largest $L$ elements in the set $\{S, i = 1, 2, \ldots, M\}$, where $L < M$ is an integer. For the convenience of latter discussion, let the ratio be marked by $r = L/M$.

**Step 5.** Determine if the image is detectable by applying thresholding test. If $S$ is greater than the decision threshold $\tau_S$, the image is detectable; else not.

Algorithm 2 Noising detection.

**Step 1.** Divide the detectable image into $8 \times 8$ blocks. Let the $i$th block be denoted by $f_{xy}$, $x, y = 0, 1, \ldots, 7$, where $x, y$ are the local coordinates in an image block.

**Step 2.** Determine if the $i$th block is a special block according to the following constrains: $\sum_{x} |V_{xy}f_{xy}| - \sum_{y} |V_{xy}f_{xy}| = 0$, where $V_{xy}$ denote the first order of difference along the row and column directions, respectively. $| \cdot |$ means to take absolute value.

**Step 3.** Count the total number of special blocks in the image and marked by $N$. Determine if noise addition has been enforced by applying thresholding test. If $N$ is smaller than the decision threshold $\tau_N$, noise addition is detected; else not.

4.1 Test Data and Performance Metric

The test data includes two image sets: (1) Uncompressed color image database (UCID) including 244 uncompressed images on various topics such as natural scenes and man-made objects, and (2) 1100 photographs captured by several digital cameras, stored in JPEG format, and with the resolution from 1200 × 900 to 2832 × 2128 pixels. The camera settings, including exposure, color balance, etc., were set automatic as this resembles what probably common users would do. The content consists of various natural scenes.

The unaltered images and their noised versions are taken as negative and positive samples, respectively. The detectable rate ($R$) is defined as the fraction of detectable samples in the all ones. The precision ($P_d$) is defined as the fraction of correctly classified samples in the set of detectable samples. The false positive rate ($P_{fp}$) and false negative rate ($P_{fn}$) are defined as the fraction of incorrectly classified samples in the detectable negative and positive sample sets, respectively.

4.2 Detection Performance via Parameters Setting

The related parameters are set as $r = 5 \times 10^{-3}$, $\tau_N = 1$ through quantitative tests. Figure 4 shows the detection results on UCID images under different $r$ values. At each $\tau_S$ value, the detection rate $R$ and the precision $P_d$ vary to the contrary with $r$. Specifically, $R$ increases while $P_d$ decreases with $r$. As a trade-off, $r = 5 \times 10^{-3}$ is selected in the following experiments. Under such a setting, $P_d$ could approximately achieve 0.80 when $R = 0.6$. $\tau_S = 1$ is set in terms of the special distribution of positive samples’ feature values, which are all zeros. As such, it can keep $P_{fp}$ as small as possible while keep $P_{fn} \equiv 0$. The setting of $\tau_S$ relies on the practical requirements on detectable rate and detection precision. Below, the results under different $\tau_S$ values are given.

4.3 Detection Performance via Image Quality

To evaluate the detection performance in the images with different qualities, the previously JPEG-compressed UCID images and their noised version are treated as negative and positive samples, respectively. The detection results are shown in Fig. 5. Overall, an acceptable performance is obtained in uncompressed images, and a rather high performance is gained for compressed ones. For example, as for the uncompression scenario, $(R, P_d)$ approximately achieves above $(0.93, 0.73), (0.68, 0.78)$, and $(0.50, 0.87)$ at $\tau_S = 0.2, 0.4$, and 0.6, respectively. In the compression scenarios with JPEG quality factor $Q = 90, 70, (R, P_d)$ reaches as highly as $(0.92, 0.90)$ and $(0.98, 0.98)$ at $\tau_S = 0.2$, respectively. Furthermore, it indicates that both detectable rate and detection precision increase with the decrease of $Q$.

The number of detectable positive and negative samples is shown in Table 1. We can see that the number decreases with the increase of $\tau_S$ from 0 to 1. The number of detectable positive samples is usually less than that of detectable negative ones, since the sparsity of noised images should be comparatively lower than that of unaltered ones.

Since the numbers of positive and negative samples in classification are different, the false positive and false negative rates should also be investigated to evaluate the overall receiver operating characteristics (ROC) performance. As shown in Fig. 5(c) and (e) for the uncompression case, $P_{fp}$ attains 0.46, 0.39, and 0.21 at $\tau_S = 0.2, 0.4$, and 0.6, respectively. While as for the compression cases, $P_{fp}$ rapidly...
decreases to a low level. For example, $P_{fp} = 0.19$ and $0.02$ at $\tau_s = 0.2$ for $Q = 90, 70$, respectively. $P_{fp}$ keeps lower than $0.03$ under middle and low quality factors, i.e., $Q \leq 70$. Note that $P_{fn}$ is always zero because all positive samples’ feature values are zeros, which are smaller than the detection threshold $r_N = 1$.

Results of the same tests on 1100 photographs set are shown in Fig. 6 and Table 2. It consistently verifies that the same high performance is achieved. For example, $P_d$ exceeds $0.90$ and $P_{fp} = 0.18$, while $R$ keeps above $0.80$. As expected, $P_d$ increases and $P_{fp}$ decreases when $R$ is reduced to some extent.

4.4 Distinguish with Other Manipulations

In this section, the capability of our proposed algorithm for distinguishing noise addition from other manipulations is evaluated detailedly. Test samples are prepared by enforcing different types of manipulations including additive Gaussian white noise addition, Gaussian blur, MF, scaling, and gamma correction on the unaltered UCID images. The scenario $r_s = 0.4$ is considered illustratively.

The number of special blocks detected in each detectable sample, $N$, is shown in Fig. 7. It shows that the noised samples definitely own $N = 0$, whereas the other samples including the unaltered ones and those processed by other...
types of manipulations mostly have quantitative special blocks, namely $N > 0$. The distinguishability between noise addition and other manipulations could be intuitively verified by such feature values’ distribution. In Fig. 8, the detectable rates in each type of sample set are indicated and mostly keep above 0.80. The proportion of the samples classified as noised ones in each type of detectable sample set, marked as $R_n$, is also indicated. It shows that the noised samples are classified correctly and with $R_n = 1$, while $R_n$ for the other types of samples is relatively small, i.e., below 0.2, especially for the unaltered, MF $3 \times 3$, scale 1.5, and gamma types. Such results demonstrate the reliability of our proposed noise addition forensics method. The designed feature metric is verified to be unique to noise addition manipulation.

### Table 1

The number of detectable samples in UCID images under various precompressions. Here, the two values parted by “/” are of positive and negative ones, respectively. “Q = 100” means uncompressed.

<table>
<thead>
<tr>
<th>$Q$</th>
<th>0.0</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>1.0</th>
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<tbody>
<tr>
<td>100</td>
<td>244/244</td>
<td>232/236</td>
<td>195/210</td>
<td>148/186</td>
<td>118/161</td>
<td>100/144</td>
<td>85/122</td>
<td>8/101</td>
<td>0/94</td>
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<td>90</td>
<td>244/244</td>
<td>231/234</td>
<td>199/215</td>
<td>145/193</td>
<td>107/174</td>
<td>94/154</td>
<td>86/135</td>
<td>11/119</td>
<td>0/115</td>
<td>0/114</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>244/244</td>
<td>238/241</td>
<td>209/223</td>
<td>187/208</td>
<td>120/199</td>
<td>92/191</td>
<td>84/188</td>
<td>10/187</td>
<td>0/187</td>
<td>0/187</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>244/244</td>
<td>241/241</td>
<td>220/230</td>
<td>201/220</td>
<td>140/216</td>
<td>86/213</td>
<td>75/212</td>
<td>7/212</td>
<td>0/212</td>
<td>0/212</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>244/244</td>
<td>241/242</td>
<td>237/240</td>
<td>229/236</td>
<td>187/236</td>
<td>99/236</td>
<td>88/236</td>
<td>11/236</td>
<td>0/236</td>
<td>0/236</td>
<td></td>
</tr>
</tbody>
</table>

### Table 2

The number of detectable positive and negative samples ($N_p$, $N_n$) in 1100 photographs set.

<table>
<thead>
<tr>
<th>$\tau_s$</th>
<th>0.0</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>1.0</th>
</tr>
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<tr>
<td>$N_p/N_n$</td>
<td>1100/1100</td>
<td>1100/1100</td>
<td>1100/1100</td>
<td>1100/1100</td>
<td>1059/1081</td>
<td>798/1035</td>
<td>390/949</td>
<td>324/793</td>
<td>273/685</td>
<td>52/579</td>
<td>0/523</td>
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Fig. 6 Detection results on 1100 photographs set. (a) Detectable rate $R$, (b) precision $P_d$, and (c) false positive rate $P_f$ vary via the sparsity threshold $\tau_s$. 
Comparison with Previous Methods

To evaluate the advantage of our proposed method, the previous method proposed in Ref. 12 for detecting global noise addition is compared with UCID dataset. As shown in Table 3, the results demonstrate that our proposed method could detect noise addition in uncompressed images to a certain extent. With the increase of $\tau_S$ from 0.2 to 0.6, the detection precision $P_d$ increases from 0.74 to 0.87, $P_{fp}$ decreases from 0.51 to 0.21, and $P_{fn} \equiv 0$. Such an achievement is obtained at the cost of decreasing the detectable rate $R$ to some extent, which changes from 0.96 to 0.50 correspondingly. However, Stamm and Liu method cannot detect noise addition in uncompressed images. In high-quality JPEG-compressed images, i.e., $Q = 90$, our proposed method could achieve comparative detection performance with limited detectable rates. In middle-quality JPEG-compressed images, i.e., $Q = 70$ and 50, the two methods gain approximately high performance. In low-quality JPEG-compressed images, i.e., $Q = 30$, our proposed method outperforms Stamm and Liu method to a certain degree. It shows that $(R, P_d, P_{fp}, P_{fn}) = (1.00, 0.89, 0.12, 0.10)$ is gained by our proposed method, whereas the relatively inferior result $(R, P_d, P_{fp}, P_{fn}) = (1.00, 1.00, 0.00, 0.00)$ is obtained by the Stamm and Liu method.

5 Conclusions

In this article, a novel scheme is proposed to detect the global noise addition in digital images. The strategy of detectable image samples is novelly designed to ensure the reliability of such a detector. Special image blocks, including the constant and strip ones, are used as the prober for identifying the trace

<table>
<thead>
<tr>
<th>$Q$</th>
<th>$R$</th>
<th>$P_d$</th>
<th>$P_{fp}$</th>
<th>$P_{fn}$</th>
<th>$R$</th>
<th>$P_d$</th>
<th>$P_{fp}$</th>
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<td>0.51</td>
<td>0</td>
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<td>0.79</td>
<td>0.38</td>
<td>0</td>
<td>0.50</td>
<td>0.87</td>
<td>0.21</td>
<td>0</td>
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<tr>
<td>90</td>
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<td>0.90</td>
<td>0.18</td>
<td>0</td>
<td>0.69</td>
<td>0.96</td>
<td>0.07</td>
<td>0</td>
<td>0.51</td>
<td>1.00</td>
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<tr>
<td>70</td>
<td>0.98</td>
<td>0.99</td>
<td>0.02</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0.58</td>
<td>1.00</td>
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</tr>
<tr>
<td>50</td>
<td>0.99</td>
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<td>0.86</td>
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<tr>
<td>30</td>
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<td>1.00</td>
<td>0</td>
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<td>0</td>
<td>0.69</td>
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Table 3 Performance comparison with Stamm and Liu method. Here, “—” denotes that the method cannot work in that scenario.
of noise addition. The formal detection scheme is integrated by the procedures of detectability recognition and noise detection. Extensive experimental results have verified the effectiveness of our proposed noise addition–detection method. It can detect the noise addition applied to both previously JPEG-compressed and uncompressed images. However, the proposed method is limited to be effective on detectable images which own a certain degree of sharpness. In the future works, extending the detectability to any natural image could be investigated in depth. The extension to detect the local noise addition and to combine this with malicious tampering identification is also an attractive working direction.

Acknowledgments
This work was supported in part by 973 Program (2011CB302204), National Natural Science Funds for Distinguished Young Scholar (61025013), National NSF of China (61272355, 61332012, and 61103198), National Distinguished Young Scholar (61025013), National NSF of Singapore (2010), National Natural Science Funds for the Innovation Team, and the Beijing Science and Technology Stars Projects in 2008 and was awarded the Jeme Tien Yow Special Prize in Science and Technology in 2009.

References

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