Detecting **Doubly Compressed Images** Based on **Quantization Noise Model** and **Image Restoration**

An example of Image Forgery

(Prof. **Chiou-Ting Hsu’s** result)
• With well-developed image editing softwares, general users could now easily enhance or edit digital image contents in various ways. However, these easy-to-use editing techniques also bring new challenges in digital forensics. Many forgery detection methods have been proposed to extract traces resulted from image forgeries, such as re-sampling [1], change of nature image statistics [2], and inconsistency in color filter array (CFA) demosaicing algorithms [3, 4] or camera sensor noise patterns [5].


Unfortunately, most of the existing methods are applicable only to **uncompressed raw images** but fail to detect forgeries on compressed images. Since nowadays **most digital images are compressed in JPEG format**, study of forgery traces on JPEG images is becoming indispensable.
• Forgeries on JPEG images often involve recompression and thus change the original compression characteristics. Most existing forgery detection techniques attempt to detect the inconsistency on compression characteristics. Some rely on the estimation of JPEG quantization table.
• In [6, 7], the primary quantization table is estimated from a doubly compressed JPEG image using histograms of individual DCT coefficients. In [8], the quantization table is estimated by quantization error minimization. Also, in [9], a maximum likelihood estimation method is proposed to estimate the JPEG quantization steps.


• However, these methods tend to obtain a poor estimate of the primary quantization table from recompressed images and thus are usually less effective to detect recompression forgeries.

• Other research uses the compression artifacts, either in spatial or frequency domain, as an inherent signature for JPEG images.
Luo et al. [10] use a spatial domain method to detect the change on symmetric property of blocking artifacts for shifted and recompressed images. Prof. Hsu’s earlier work [11] analyses the blocking artifacts from their periodicity and proposes a blocking periodicity model to detect whether an image has been cropped and recompressed or not.


In frequency domain analysis, Benford’s law has been used to model the statistic change on DCT coefficients caused by recompression [12, 13]. Also, He et al. [14] proposed to detect and locate doubly compressed regions via DCT coefficient analysis.


• However, although these frequency domain methods try to detect the change on DCT distributions, these methods may fail to detect the recompression forgeries when a JPEG image has been spatially shifted or cropped with misaligned block boundaries from the original image.
• On the other hand, the spatial domain methods, which rely on detecting the abnormality of blocking artifacts, may fail to detect the recompression forgeries without any shifted or misaligned block boundaries.
Recently, Farid [15] pointed out that JPEG ghosts property may reveal the trace of recompression. Assume we recompress a compressed image with different quality factors and measure the difference of DCT coefficients before and after the recompression for each setting.

Then this difference (i.e. the JPEG ghosts) is minimized when the recompression quality factor is the same as the primary quality factor.

Although the idea is simple, this approach needs an exhaustive test for all possible compression quality factors. In addition, once the forged regions have been shifted with misaligned block boundaries, one will have to detect the JPEG ghosts for all 64 possible alignments.
• In her work, Prof. Hsu proposes to model the compression characteristics in terms of quantization errors and will demonstrate that the proposed model indeed characterizing the change caused by recompression, either with or without misaligned block boundaries.
• While Prof. Hsu adopts the proposed model to detect the doubly recompression forgeries, she needs to measure the quantization noises between the test JPEG image and its uncompressed version.

• Since it is impractical to assume that the uncompressed image is available during forgery detection, in this work, Prof. Hsu further proposes to approximate the uncompressed ground truth image using image restoration techniques.
II. QUANTIZATION NOISE MODEL

• In JPEG lossy compression, the quantization error, which is the difference between the original signal and the quantized digital value, is usually treated as the compression distortion.

• Here, another perspective is introduced to analyze the quantization noise for single and doubly compressed images.
We first model the quantization noise as

$$Ax = c = c' + n' = c'' + n'' ,$$  \hspace{1cm} (1)

where \( A \) is a 64x64 DCT component basis matrix, \( x \) is the original intensity of one 8x8 block, \( c \) is the DCT coefficients vector, \( c' \) and \( c'' \) are the quantized DCT coefficients vectors after first and second compression, respectively, and \( n' \), \( n'' \) are their corresponding quantization noises.
In (1), the quantized DCT coefficients $c'$ and $c''$ are represented by

$$c'_i = q'_i \cdot \text{round}\left[ \frac{c_i}{q'_i} \right], \quad \text{and}$$

$$c''_i = q''_i \cdot \text{round}\left[ \frac{c'_i}{q''} \right], \quad (2)$$

where $q'$, $q''$ are the corresponding quantization steps, and $i$ indicates the index of the 64 DCT components.
• In equation (1), our goal is to analyze the difference between $n'$ and $n''$. The quantization constraint set (QCS) theorem [16] showed that the un-quantized DCT coefficient should be bounded by

$$c' - \left\lfloor \frac{q'}{2} \right\rfloor \leq c \leq c' + \left\lceil \frac{q'}{2} \right\rceil.$$  \hfill (3)

In other words, the quantization noise $c - c'$ is bounded by the quantization interval. Similarly, we could also derive the quantization noise of double compression by

$$\left[-\left\lfloor \frac{q''}{2} \right\rfloor \right] \leq c' - c'' \leq \left\lfloor \frac{q''}{2} \right\rfloor.$$
Combining equations (3) and (4), we obtain

\[-\left(\left\lfloor \frac{q'}{2} \right\rfloor + \left\lfloor \frac{q''}{2} \right\rfloor\right) \leq c - c'' \leq \left\lfloor \frac{q'}{2} \right\rfloor + \left\lfloor \frac{q''}{2} \right\rfloor.\]  

(5)

From equation (5), the quantization noise between $c''$ and $c$ is now no longer bounded by the last quantization step $q''$. 
• Assume the un-quantized DCT coefficient $c$ is available, since we could obtain the quantization step $q''$ from the JPEG header, we could then distinguish whether the quantization noise of each DCT coefficient follows QCS theorem or not.
Fig. 1 shows the histogram of quantization noises of the first AC term after single and double compression, respectively. In Fig. 1(a), \( q' = 5 \), thus the quantization noise is bounded by \([-2,2]\).
In Fig. 1(b), although the quantization step $q''$ obtained from the JPEG header is also 5, from equation (5) and given that the primary quantization step $q' = 12$, the quantization noise $n''$ is no longer bounded by [-2,2] and does not follow the QCS theorem anymore.
• Note that, here the distribution is a little bit different from what calculated by equation (5) because the computation of FDCT and IDCT in the second compression may result in rounding errors.
• Fig. 1. The quantization noise histogram of 1st AC term: (a) single compression case, quantization step=5; (b) double compression case, 1st quantization step=12, 2nd quantization step=5; and (c) triple compression case, 1st quantization step=12, 2nd quantization step=7, 3rd quantization step=5.
Fig. 2 shows the probability distribution functions (pdfs) of quantization noises of the first nine DCT terms in Zig-Zag scan order. Similar to Fig. 1, the pdf after single compression is nearly uniform and bounded by the quantization interval. On the other hand, the pdfs of quantization noises after double compression behave more like Gaussians.
Fig. 2. The pdfs of quantization noises of the first 9 DCT terms, where the thin red line indicates the single compression case, and the thick blue line indicates the double compression case: (a) DC term; and (b)-(i) the 1st-8th AC terms.
• We now explain the two different pdfs from a theoretical perspective.

• Assume the two quantization noises $c - c'$ and $c' - c''$ after each single compression are two independent uniform distributions. Thus, the density of the quantization noise $c - c''$ after double compression equals the convolution of the two uniform densities $c - c'$ and $c' - c''$ [17].
Moreover, if further recompression is conducted on the image, then the pdf of the quantization noise between the final DCT coefficient and its un-quantized coefficient would be the convolution of a sequence of uniform densities and become a near Gaussian.

For example, as shown in Fig. 1(c), the quantization noise distribution of a triple compressed image is indeed more like Gaussian than the double compression case in Fig. 1 (b).
• Therefore, we could characterize the distributions of quantization noises for single compression and recompression with completely different models.

• Note that, this difference becomes less obvious for high frequency DCT terms, because most higher frequency DCT coefficients are quantized to zero after the first quantization.

From the above discussion, Prof. Hsu proposes to model the quantization noise distributions for **single compression and recompression** by **uniform** and **Gaussian** distributions, respectively.

Let $\omega_1$ denote the single compression and $\omega_2$ denote the double compression. Prof. Hsu formulates the quantization noises of each DCT coefficient as
where $n_{k,i}$, is the quantization noise of the $i$-th DCT coefficient of the $k$-th 8x8 block.
We assume each DCT component is statistically independent and formulate the quantization noises for each DCT block as

\[
p(n_k | \omega_1) = \prod_{i=1}^{\dim} p(n_{k,i} | w_1) = \prod_{i=1}^{\dim} U(c_{k,i} - \hat{c}_{k,i}, \left\lfloor \frac{q_i}{2} \right\rfloor, \left\lceil \frac{q_i}{2} \right\rceil),
\]

and

\[
p(n_k | \omega_2) = \prod_{i=1}^{\dim} p(n_{k,i} | w_2) = \prod_{i=1}^{\dim} N(c_{k,i} - \hat{c}_{k,i}, 0, \sigma_i^2).
\]

In (7), \(\hat{c}_{k,i}\) indicates the \(i\)-th quantized DCT coefficient of the \(k\)-th block, and \(c_{k,i}\) is its original un-quantized coefficient.
• The constant $\text{dim}$ indicates the number of DCT components in zig-zag scan order included in this model. Prof. Hsu set $\text{dim} = 15$ in the following experiments.

• Assume the un-quantized coefficients $c_{k,j}$ is available, Prof. Hsu first measures the unknown parameter $\sigma_i^2$ in equation (7) using the iterative algorithms such as EM.
• Next, from equation (7), Prof. Hsu obtains the posterior probability of each block:

\[
p(\omega_2 | n_k) = \prod_{i=1}^{\text{dim}} p(w_2 | n_{k,i}) = \prod_{i=1}^{\text{dim}} \frac{p(n_{k,i} | w_2)}{p(n_{k,i} | w_1) + p(n_{k,i} | w_2)}.
\]
Fig. 3 shows two recompression forgery examples, with aligned and misaligned block boundaries, and their corresponding posterior maps.

In either case, the proposed quantization noise model successfully characterizes the difference between the doubly compressed region and the single compressed surrounding area. Moreover, the results also show that this model is very insensitive to image content.
Fig. 3. (a) A forgery example with block alignment; (b) the posterior map of (a); (c) a forgery example with block misalignment, where the cropped position equals to (3,2); and (d) the posterior map of (c). The white pixel indicates that the probability equals 1, and black pixel indicates 0.
III. GROUND TRUTH ESTIMATION BASED ON IMAGE RESTORATION

• In Sec. II, Prof. Hsu introduced a new and robust quantization noise model to characterize the differences between single and double compressions. The only difficulty to be resolved now is: where can one get the original and un-quantized image?

• Since the only information one has is the JPEG image, Prof. Hsu then proposes to approximate the ground truth image from the JPEG image using the image restoration techniques.
• The estimated ground truth should have similar properties to uncompressed images. In other words, the compression distortions, such as blocking artifacts, ringing artifacts, color distortion, and loss of high frequency details, should be eliminated or compensated.
Fig. 4 shows the framework of Prof. Hsu’s approach.
A. Deblocking

• Deblocking process is the most intuitive method to eliminate compression distortions. Most existing approaches are applied on spatial domain by filtering only the image pixels around block boundaries.

• Although the spatial-domain deblocking approaches achieve good performance in visual quality, these methods usually fail to recover the true pixel values because the quantization noise affects not only the boundary pixels but the whole 8x8 block.
Moreover, since Prof. Hsu’s quantization noise model is formulated in DCT domain, here, she adopted the DCT-domain deblocking method [18]. Consider one DCT block $b$ and its one-pixel diagonally-shifted block $b'$. From [18], the shifted block $b'$ should have more nonzero values in high order AC terms than $b$ because of the blocking artifacts.
• Also, both $b'$ and $b$ should still have similar high frequency information.

• Therefore, the DCT-domain deblocking process would adjust the number of nonzero AC terms of $b'$ according to $b$. Prof. Hsu modifies this approach for her ground truth approximation by the following three steps.
• **Step 1**: Adjust the number of nonzero AC terms of $b'$ according to $b$ [18].

• **Step 2**: For each block $b$, project the DCT coefficients to a convex set according to QCS.
• **Step 3**: Repeat step 1, until the DCT coefficients of all blocks are no longer changed.

\[
 c_{k,i} = \begin{cases} 
 \hat{c}_{k,i} + \left[ \frac{q_i}{2} \right], & \text{if } c_{k,i} > \hat{c}_{k,i} + \kappa \times \left[\frac{q_i}{2}\right] \\
 \hat{c}_{k,i} - \left[ \frac{q_i}{2} \right], & \text{if } c_{k,i} < \hat{c}_{k,i} - \kappa \times \left[\frac{q_i}{2}\right] \\
 c_{k,i}, & \text{otherwise} 
\end{cases}
\] (9)
• In equation (9), the parameter $\kappa$ is chosen as 3 in Prof. Hsu’s experiment because she assumes the quantization noise of double compression would not exceed three times of the quantization interval.

• Fig. 5 shows the quantization noise distribution measured using the deblocked image as the estimated ground truth and the one with the un-quantized ground truth.
Fig. 5. The quantization noise distributions, where the 1\textsuperscript{st} row is obtained when the ground truth is available, and the 2\textsuperscript{nd} row is obtained with the estimated ground truth after the deblocking process: (a) DC term; (b) 2\textsuperscript{nd} AC term; (c) 4\textsuperscript{th} AC term; and (d) 8\textsuperscript{th} AC term.
• From Fig. 5, with the deblocked DCT coefficients, the difference in quantization noise distribution for single and double compression cases, though different from the ideal case, is still distinguishable.
B. Low frequency compensation

• In addition to blocking artifacts, another compression distortion is the loss of higher frequency detail.

• Research on image restoration has pointed out that it is almost impossible to predict the original higher frequency detail without any prior knowledge.

• Therefore, many learning-based methods have been introduced to deal with this problem.
• The **codebook design in vector quantization (VQ)** methods is useful to represent general **higher frequency contents**, such as texture or edge. Here, the VQ based approach [19] for reliable **ground truth approximation** is adopted.

Nevertheless, Prof. Hsu’s experiments show that high frequency compensation (HFC) usually results in poor performance. The reason is because VQ based approach attempts to compensate high frequency detail in terms of visual quality but not in terms of accuracy.

Moreover, most traditional compensation methods are conducted in spatial domain and are often less effective on DCT coefficients.
• Therefore Prof. Hsu modified the method proposed in [19] and compensated the DCT coefficients directly.

• In addition, instead of HFC, Prof. Hsu introduces the idea of low frequency compensation (LFC). Only the first fifteen DCT coefficients in zig-zag scan order would be compensated.
• Fig. 6 shows the distributions of quantization noise magnitude. The quantization noise distribution after low frequency compensation now better approximates the ideal case.
Fig. 6. The magnitude distribution of quantization noise; where the 1st row is obtained with ground truth, the 2nd row is obtained with the estimated ground truth after deblocking process, and the 3rd row is obtained with the estimated ground truth after deblocking and low frequency compensation: (a) DC term; (b) 1st AC term; (c) 5th AC term; and (d) 10th AC term.
C. Modification of quantization noise model

• Although Prof. Hsu approximates the ground truth with the above two steps, the quantization noise distribution still behaves differently from the ideal cases discussed in section II.

• Especially in single compression case, the quantization noise measured with the estimated ground truth is no longer bounded by the quantization interval, as described in equation (3).
Prof. Hsu observed that the approximated quantization noise usually ranges across the quantization interval but still concentrates to zero like a Laplacian distribution. Therefore, she modified her quantization model for single compression $\omega_1$ using the more general Laplacian distribution:

$$p(n_k | \omega_1) = \prod_{i=1}^{\text{dim}} p(n_{k,i} | w_1) = \prod_{i=1}^{\text{dim}} L(\hat{c}_{k,i} - c_{k,i} | 0, q_i) \cdot \text{(10)}$$
IV. EXPERIMENTAL RESULTS

• **A. Robustness of quantization model**

To verify the robustness of the proposed quantization noise model, here Prof. Hsu first assumes that the un-quantized ground truth images are available during the forgery detection. She also compares with two existing approaches [7] and [15], where the method in [7] relies on estimation of primary quantization table and the method in [15] relies on exhaustively recompressing the test image using every possible primary quality factor, and both are able to locate forged regions.
• In order to have a fair comparison, here we assume the primary quantization table and quality factor are known.

• In this experiment, each image size is 1024x1024. Prof. Hsu first crops a subimage with size 480x480 and compresses this subimage with JPEG quality factor $QF_1$. Next, She copies this compressed subimage back into the original raw image and then compresses the spliced image with JPEG quality factor $QF_2$. 
• Prof. Hsu tested 500 images for each quality setting $QF_1$ and $QF_2$ and derive a ROC curve for each test image. Fig. 7 shows the averaged ROC curve when $QF_1$ equals to 50. From Fig. 7, the proposed quantization noise model achieves high performance in detecting the copy-paste-recompression forgery.
Fig. 7. The averaged ROC curves, where the primary quality factor (QF1) equals to 50 and each quality setting has 500 forged images.
Table 1 shows the detection accuracy of each quality setting. Here we use the averaged area of ROC curve to measure the detection rate. When $QF_1 < QF_2$, the detection accuracy are almost close to 100%; while $QF_1 > QF_2$, the detection accuracy ranges from 60% to 90%.
• The degraded performance in the case of $QF_1 > QF_2$ is because the quantization noise is dominated by the quantization step of the second compression and become less distinguishable between single and double compression cases. Note that, when $QF_1 = QF_2$, since the DCT coefficient does not change after recompression, this recompression case is not detectable with the proposed quantization noise model.
Table 1 also compares the detection rates with the two approaches [7] and [15].

Except for $QF_1 = QF_2$, the proposed quantization noise model all achieves the best performance.
B. Forgery detection based on image restoration

- Using the framework of Fig. 4, Prof. Hsu approximated a reliable ground truth image and applied it to forgery detection.

- Fig. 8(a) shows a compressed image before image restoration, and Fig. 8(b) shows the difference between Fig. 8(a) and its restored result. The artifacts around block boundaries are now eliminated and the image details are also enhanced.
Fig. 8. (a) A compressed image with quality factor 80; (b) the difference map between (a) and its restored result; and (c) the enlarged view of the small square in (b).
Fig. 9 shows the detection result, where the forged region in Fig. 9(a) is first compressed with quality factor 50 and then recompressed with quality factor 80. Fig. 9(b) indicates the posterior map, where the forged region is clearly identified.
Fig. 9. (a) A forged image, where the red square indicates the forged region; and (b) the posterior map of (a).
Table 1. Detection accuracy(%) which indicates the average of ROC curve. For each quality setting, there are 500 forged images.

<table>
<thead>
<tr>
<th>QF1</th>
<th>QF2</th>
<th>50</th>
<th>60</th>
<th>70</th>
<th>80</th>
<th>90</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>Proposed</td>
<td>49.0</td>
<td>83.7</td>
<td>94.7</td>
<td>98.3</td>
<td>99.4</td>
</tr>
<tr>
<td></td>
<td>[7]</td>
<td>58.5</td>
<td>62.2</td>
<td>82.0</td>
<td>93.2</td>
<td>98.7</td>
</tr>
<tr>
<td></td>
<td>[15]</td>
<td>0.84</td>
<td>59.3</td>
<td>84.0</td>
<td>94.0</td>
<td>96.8</td>
</tr>
<tr>
<td>60</td>
<td>Proposed</td>
<td>76.8</td>
<td>49.1</td>
<td>89.9</td>
<td>97.8</td>
<td>99.5</td>
</tr>
<tr>
<td></td>
<td>[7]</td>
<td>42.6</td>
<td>56.5</td>
<td>66.6</td>
<td>94.6</td>
<td>98.1</td>
</tr>
<tr>
<td></td>
<td>[15]</td>
<td>45.8</td>
<td>1.12</td>
<td>72.7</td>
<td>96.6</td>
<td>97.0</td>
</tr>
<tr>
<td>Angle (°)</td>
<td>Proposed</td>
<td>70</td>
<td>80</td>
<td>90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>----------</td>
<td>----------</td>
<td>----</td>
<td>----</td>
<td>----</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[7]</td>
<td>34.5</td>
<td>38.6</td>
<td>56.8</td>
<td>76.4</td>
<td>97.4</td>
</tr>
<tr>
<td></td>
<td>[15]</td>
<td>37.8</td>
<td>41.3</td>
<td>1.92</td>
<td>74.3</td>
<td>95.1</td>
</tr>
<tr>
<td>70</td>
<td>Proposed</td>
<td>82.7</td>
<td>84.1</td>
<td>49.2</td>
<td>95.7</td>
<td>99.5</td>
</tr>
<tr>
<td></td>
<td>[7]</td>
<td>34.5</td>
<td>38.6</td>
<td>56.8</td>
<td>76.4</td>
<td>97.4</td>
</tr>
<tr>
<td></td>
<td>[15]</td>
<td>37.8</td>
<td>41.3</td>
<td>1.92</td>
<td>74.3</td>
<td>95.1</td>
</tr>
<tr>
<td>80</td>
<td>Proposed</td>
<td>66.1</td>
<td>89.4</td>
<td>88.5</td>
<td>49.4</td>
<td>99.2</td>
</tr>
<tr>
<td></td>
<td>[7]</td>
<td>59.9</td>
<td>45.1</td>
<td>33.9</td>
<td>57.3</td>
<td>97.5</td>
</tr>
<tr>
<td></td>
<td>[15]</td>
<td>47.6</td>
<td>39.5</td>
<td>32.8</td>
<td>4.03</td>
<td>94.2</td>
</tr>
<tr>
<td>90</td>
<td>Proposed</td>
<td>57.2</td>
<td>66.1</td>
<td>65.4</td>
<td>93.7</td>
<td>49.9</td>
</tr>
<tr>
<td></td>
<td>[7]</td>
<td>53.7</td>
<td>52.4</td>
<td>52.1</td>
<td>53.0</td>
<td>57.9</td>
</tr>
<tr>
<td></td>
<td>[15]</td>
<td>40.5</td>
<td>40.5</td>
<td>44.2</td>
<td>40.5</td>
<td>12.8</td>
</tr>
</tbody>
</table>