An Approach to Detecting JPEG Down-Recompression and Seam Carving Forgery under Recompression Anti-forensics

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Abstract

In multimedia forensics, the detection of forgery on joint photographic experts group (JPEG) images is an interesting and challenging work. JPEG double compression, one of common operations that may occur in the tampering manipulation, has been widely studied. While the quality of the second compression is higher than the quality of the first compression, most approaches have obtained effective detection results, however, it still falls short of accurately detecting the down-recompression that the second compression quality is lower than the first compression quality.

Seam carving was originally designed for content-aware image resizing. While it is widely used in computer vision and multimedia processing for legitimate applications, it is also being used for forgery manipulation. Although several methods have been proposed to detect seam carving-based forgery, to this date, the detection of the seam carving forgery under recompression in JPEG images has not been well explored.

To address the highly challenging detection problems described above, we proposed a large feature mining-based approach. Over one hundred thousand features from the spatial domain and from the DCT transform domain are developed. Ensemble learning is used to deal with the high dimensionality and to avoid overfitting that may occur with some traditional learning classifier for the detection. Our study demonstrates the efficacy of proposed approach to discriminating JPEG

down-recompression and exposing the seam-carving forgery from the same quality and low quality JPEG recompression. And hence, it fills a gap in image forensics.

Key Words: Seam carving, down-recompression, down-scaling, image forensics, large feature mining

1. INTRODUCTION

While being widely facilitated and proliferated by digital techniques, digital multimedia can be easily manipulated without leaving any obvious clue. Multimedia forensics has emerged as new and interesting discipline wherein steganalysis and forgery detection are two interesting areas with broad impact to each other. While multiple promising and well-designed steganalysis methods have been proposed and several steganographic systems have been successfully steg-analyzed [10, 14, 15, 16, 20, 22, 30], it seems that the advance in forgery detection falls behind.

As a standardized lossy compression, JPEG is a most popular digital image format and standard in our daily life. JPEG image-based forensics has become one of hot spots in multimedia forensics. In terms of the manipulation of JPEG image forgery, generally, the tampering involves several basic operations, such as image resize, rotation, splicing, and double JPEG compression. The detection of these fundamental manipulations and relevant forgery has been actively explored [2, 3, 5, 7, 8, 11, 12, 13, 17, 19, 22, 23, 25, 26, 30]. For example, double JPEG compression is one of most adopted manipulations. While we decode the bit stream of a JPEG image and implement the manipulation in spatial domain, and then compress the modified image back to JPEG format, if the newly adopted quantization table is different from the one used by original JPEG image, the modified JPEG image is processed through double JPEG compression. Although JPEG double compression does not by itself prove malicious or unlawful tampering, it is an evidence of image manipulation. The detection of double JPEG compression has been widely conducted [2, 3, 5, 7, 8, 12, 19, 23]. In general, the

detection is very effective while the second compression quality is higher than the first compression quality, however, it is not well while the second compression quality is lower than the first compression quality. Being aware of the weakness of the detection methods, a forgery maker may manipulate JPEG images in spatial domain and then save the tampered images at lower image qualities, in order to evade from being detected.

In addition to JPEG-double compression, the detection of several popular tampering types, including region duplication (copy paste and the variants), image splicing, and seam carving-based forgery were proposed [4, 11, 27, 28, 32, 33, 34].

Seam carving, also known as image retargeting, content-aware scaling, liquid resizing or liquid rescaling, is a method developed for image resizing [1]. The idea behind the image resizing is to establish a number of paths of least importance, called seams in an image or video file for both reduction and expansion. A seam is an optimal 8-connected path of pixels on a single image from top to bottom, or left to right. Seam carving allows manually defining areas in which pixels may not be changed and features the ability to erase entire objects from an image/photo. Seam carving has been implemented in Adobe Photoshop and other popular computer graphic applications including GIMP, digiKam, ImageMagic, and iResizer. The proliferation of seam carving rises a serious challenge in image forensics.

Regarding seam carving-based image forgery detection, Sarkar et al. [28] utilized a steganalysis detector, which was originally developed to detect JPEG-based steganograms [30], to expose seam-carved (or seam-inserted) from untouched images. Fillion and Sharma [9] designed a method to detect seam-carved images including benign image reduction, benign image enlargement, and deliberate image reduction. They tested their method over a set of images consisting of 1484 uncompressed images. Unfortunately, the JPEG images after content-aware manipulation were not tested. Inspired by the idea in detecting cropping and recompression as well as relevant copy-paste forgery [19], Liu and Chen also applied neighboring joint density that was used in steganalysis [18]

and the calibrated version to detect seam carving-based forgery in JPEG images and obtained promising detection performance [22]. Chang et al. proposed a method to detect seam carving in JPEG images based on the symmetrical property of blocking artifact characteristics matrix (BCAM) and the extension [4]. Wei et al. proposed a patch analysis method to detect seam carving [32], Ryu and Lee designed a method to discriminate seam carving from intact by energy bias and noise features [27]. Recently, Yin et al. proposed a method to expose seam carving forgery by combining half-seam features, energy bias and noise-based feature together from the local binary pattern [33]. Although several methods have been proposed to detect seam carving-based image forgery, the effort to expose the tampering under recompression anti-forensics is still underperformed, as it is very challenging especially in detecting the seam carving forgery under down-recompression anti-forensics manipulation.

To resolve the detection problems, inspired by the success of large feature mining in steganography detection [10, 14], based on our previous study in image forgery detection and steganalysis [19, 22], we propose a large scale feature mining-based approach. Ensemble learning is employed for the detection. Our experimental results prove the effectiveness of our approach. In the followings, section 2 describes the background and the problem, section 3 gives the details of our detection methods, section 4 presents our experiments and analysis, followed by conclusions in section 5.

2. PROBLEM DESCRIPTION

2.1 JPEG Down-Recompression

In JPEG compression, it shows that the marginal density of DCT coefficients at each frequency approximately follows the generalized Gaussian distribution (GGD) [29], given by

$$\rho(x; \alpha, \beta) = \frac{\beta}{2\alpha\Gamma(1/\beta)} \exp\left\{-\left(|x|/\alpha\right)^\beta\right\} \quad (1)$$

Where $\Gamma(\cdot)$ is the Gamma function, scale parameter α models the width of the PDF peak, and shape parameter β models the shape of the distribution.

JPEG double compression may changes the marginal density and the modification depends on the first compression quality and the second compression quality. Fig. 1 demonstrates a singly compressed JPEG image with quality ‘75’ (a), doubly compressed JPEG images of the first compression quality ‘55’ (b) and ‘90’ (c) respectively, followed by the second compression quality factor ‘75’ at the first row. The marginal densities are plotted on the frequency coordinate (1,0) at the second row, on the frequency coordinate (1,1) at the third row, and on the frequency coordinate (0,2) at the fourth row. The marginal densities on the double compression from a lower first quality factor ‘55’, shown in Fig. 1(e), (h), and (k), clearly demonstrate the periodical gaps. However, the marginal density on the double compression from a higher first quality factor ‘90’, as shown by Fig. 1(f), (i), and (l), is not such noticeable.

Fig 1. Marginal densities of a single compression (left) and double compressions (middle and right). X-axis and y-axis give the values of the DCT coefficients and the occurrences.

In the detection of JPEG double compression, while the first compression quality is lower than the second compression quality, most detection methods are very effective. However, these methods are not well while the first compression quality is higher than the second compression quality. That is, the detection of JPEG down-recompression are not effective, especially while the first compression quality is considerably higher than the second compression quality [2, 5, 24].

To detect double JPEG compression with the same quantization matrix, the authors in [12] designed a method based on an observation, that is, in the process of recompressing a JPEG image with the same quantization matrix over and over again, the number of different JPEG coefficients between the two consecutive versions will monotonically decrease in general. There are, however, serious flaws with the method. Firstly, the observation is far from being always true. For example, by using the image database in the references [15, 16, 18], there are about 20% JPEG images without any modification of the quantized DCT coefficients between the first compression and the second compression by using the same quantization matrix. In other words, the foundation of the detection method designed in [12] may not be statistically sound. We proposed a method based on shift-recompression [19] to detect the misaligned forgery on the same quantization in JPEG images. Our study shows that different shift recompressions with/without different cropping demonstrate different characteristics. In the comparison to the detection method [24], our previous method significantly improved the detection accuracy by about 32% to 45% [19]. However, the method was not examined for the detection of JPEG down-recompression [19].

Being aware of the weakness of existing image forgery methods and powerless in detecting JPEG down-recompression, a forgery producer may manipulate a JPEG image in spatial domain, and then save the doctored JPEG image at a lower image quality. In such a case, the image tampering followed by JPEG down-recompression becomes very hard from being detected.

2.2 Seam Carving and Recompression Anti-forensics

In seam carving, to achieve content-aware scaling, unnoticeable pixels on the least important seams that blend with their surroundings are removed or inserted. Formally, let $\mathbf{I}$ be a $p \times q$ image and a vertical seam is defined by:

$$S^X = \{s_i^x\}_{i=1}^p = \{(x(i), i)\}_{i=1}^p, \quad (2)$$

$$\text{s.t. } \forall i, |x(i) - x(i-1)| \leq 1$$

where x is a mapping $x: [1, \dots, p] \rightarrow [1, \dots, q]$. Similarly, a horizontal seam is defined by:

$$S^Y = \{s_j^y\}_{j=1}^q = \{(j, y(j))\}_{j=1}^q, \quad (3)$$

$$\text{s.t. } \forall j, |y(j) - y(j-1)| \leq 1$$

where y is a mapping $y: [1, \dots, q] \rightarrow [1, \dots, p]$.

The pixels of the path of seam S is denoted as $\mathbf{I}_S$. Given an energy function e , the cost of a seam is calculated by $E(S) = E(\mathbf{I}_S) = \sum_{i=1}^p e(I(S_i))$. The optimal seam S^* generally minimizes the seam cost:

$$S^* = \min_S E(S) = \min_S \sum_{i=1}^p e(I(S_i)) \quad (4)$$

In the reference [1], several image importance measures are examined as the energy function. Although no single energy function performs well across all images but in general the following two measures e_1 and e_{HoG} work quite well.

$$e_1(I) = \left| \frac{\partial}{\partial x} I \right| + \left| \frac{\partial}{\partial y} I \right| \quad (5)$$

$$e_{HoG}(I) = \frac{\left| \frac{\partial}{\partial x} I \right| + \left| \frac{\partial}{\partial y} I \right|}{\max(HoG(I(x, y)))} \quad (6)$$

Where $HoG(I(x, y))$ is a histogram of oriented gradients at every pixel [6].

While seam carving has been widely used for content aware image resizing, it is also used for tampering illusion such as removing or inserting some objects. Figure 2 shows one untouched image on the left and doctored image by seam carving on the right.

Fig. 2. An example of image tampering by seam carving.

After seam carving, it is very easy for a forgery maker to save manipulated images in JPEG format. Given original JPEG image quality QF_1 (before tampering) and the manipulated image quality QF_2 (after seam carving in spatial domain and then saving in JPEG format), while the quality QF_2 is lower than QF_1 , the following low-quality JPEG recompression may significantly destroy or compromise the traces left by seam carving. To our knowledge, while the manipulated images are saved at a lower-level JPEG quality, the examination has not been investigated literally.

3. PROPOSED APPROACH

3.1 Background

We designed a neighboring joint density-based approach to detecting JPEG steganography [16, 18] and calibrated neighboring joint density to improve the detection of steganography in JPEG images [22]. The calibrated neighboring joint density under different shift-recompressions is also used to detect the content-aware-based tampering in JPEG images on the same quantization [22].

Although neighboring joint density-based approach is successful in detecting steganography, JPEG-based resize, and JPEG double recompression, unfortunately, the existing approach only considers the mean joint density over the entire DCT frequency subbands, it essentially ignores the discrimination capacity that is directly contributed by each individual frequency subband. In our opinion, firstly, different features from different frequency subbands may play different roles in distinguishing different operations in JPEG image forensics. The average processing skips such decent discriminative information. Secondly, in JPEG compression, the quantization steps at different frequency coordinates are different, the feature extraction based on average processing ignores such a basis. Thirdly, in the previous approach [22], the calibration features are calculated by averaging the features of all 63 shift-recompressions. We have demonstrated that different shift compressions may have different characteristics [19]. In this paper, our proposed big novel feature mining will overcome these weakness.

3.2 Correlation of Adjacent DCT Coefficients

Regarding the statistical modeling in the DCT domain, there is no argument that the marginal density of the DCT coefficients adheres to the Generalized Gaussian Distribution (GGD); however, there is no conclusive agreement about the exact modeling of the joint density of the DCT coefficients. Our study shows that neighboring quantized DCT coefficients of natural JPEG images are correlated and the correlations are different at different individual frequency sub-bands. We examined 10000 JPEG

photos with the quality factor of 70. These photos were originally obtained in the raw format by using four different bands of digital cameras. The average correlation coefficients of the absolute values of the quantized DCT coefficients to the right adjacent neighbors are listed in Table I(a), showing the weak correlation among adjacent DCT coefficients. To make a comparison, we also produce 5000 random images wherein the pixel values are randomly generated by computers. We convert these images into JPEG format at the quality 70. Table I(b) shows the same correlation coefficients based on the 5000 images. The value at the i^{th} row and the j^{th} column in the table shows the coefficient correlations of the absolute array between the frequency subband at $(i-1, j-1)$ and the subband at $(i-1, j)$, for instance, the value 0.43 in Table I(a) is the correlation coefficient of the absolute DCT array between the frequency subband at $(0,1)$ and the subband at $(0, 2)$, and so on.

Table I. The average correlation coefficients of the absolute DCT array at different individual frequency subbands, based on 10000 JPEG photos (a), and 5000 randomly generated images (b).

(a) Neighboring correlation coefficients (natural photos)

	0.43	0.41	0.36	0.26	0.17	0.12
0.31	0.33	0.31	0.25	0.14	0.13	0.11
0.30	0.30	0.26	0.19	0.14	0.09	0.10
0.27	0.24	0.20	0.14	0.09	0.07	0.07
0.23	0.16	0.12	0.11	0.09	0.04	0.13
0.16	0.10	0.08	0.07	0.06	0.06	0.29
0.10	0.06	0.06	0.08	0.14		

(b) Neighboring correlation coefficients (random images)

	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00

Fig. 3 shows two JPEG images at the quality of “75” and the neighboring joint densities of the quantized DCT coefficients at different frequency coordinates. It demonstrates that, the neighboring

joint density is generally different at different frequency coordinates, it is also different across different images. Additionally, the density is approximately symmetric to the lines $x=0$ and $y=0$.

Fig. 3. Neighboring joint densities of two JPEG images at different DCT frequency subbands.

3.3 Statistical Modification by JPEG Down-recompression and relevant operations

While JPEG compression is performed to a never compressed image, the DCT coefficients before quantization and after quantization are denoted pc_{mn} and c_{mn} respectively at the frequency coordinate (m, n) ($m=0, 1 \dots 7$; $n=0, 1 \dots 7$), the quantization step is denoted Q_{mn} , and $R(\bullet)$ denotes the round function.

$$c_{mn} = R \left(\frac{pc_{mn}}{Q_{mn}} \right) \quad (7)$$

We have

$$-0.5 \leq \frac{pc_{mn}}{Q_{mn}} - R \left(\frac{pc_{mn}}{Q_{mn}} \right) < 0.5, \text{ or } (c_{mn} - 0.5)Q_{mn} \leq pc_{mn} < (c_{mn} + 0.5)Q_{mn}$$

As for down-recompression, the quantization steps at the first and the second compression are denoted by $Q_{mn}^{(1)}$ and $Q_{mn}^{(2)}$ ($Q_{mn}^{(1)} < Q_{mn}^{(2)}$, $Q_{mn}^{(2)} = Q_{mn}$). Without losing a generality, suppose c_{mn} is positive, the quantized DCT coefficient after down-recompression is denoted by $c_{mn}^{(2)}$, here we ignore the truncating error,

$$c_{mn}^{(2)} = R \left(R \left(\frac{pc_{mn}}{Q_{mn}^{(1)}} \right) \bullet \frac{Q_{mn}^{(1)}}{Q_{mn}^{(2)}} \right) \quad (8)$$

Let

$$c_{mn}^{(1)} = R \left(\frac{pc_{mn}}{Q_{mn}^{(1)}} \right) \quad (9)$$

Then,

$$c_{mn}^{(2)} = R \left(\frac{c_{mn}^{(1)} Q_{mn}^{(1)}}{Q_{mn}^{(2)}} \right) \quad (10)$$

$$c_{mn}^{(2)} = \begin{cases} c_{mn} - 1, & c_{mn}^{(1)} Q_{mn}^{(1)} < (c_{mn} - 0.5) Q_{mn}^{(2)} \leq pc_{mn} < (c_{mn}^{(1)} + 0.5) Q_{mn}^{(1)} \\ c_{mn}, & (c_{mn} - 0.5) Q_{mn}^{(2)} \leq c_{mn}^{(1)} Q_{mn}^{(1)} < (c_{mn} + 0.5) Q_{mn}^{(2)} \\ c_{mn} + 1, & (c_{mn}^{(1)} - 0.5) Q_{mn}^{(1)} \leq pc_{mn} < (c_{mn} + 0.5) Q_{mn}^{(2)} \leq c_{mn}^{(1)} Q_{mn}^{(1)} \end{cases} \quad (11)$$

As indicated by equation (11), compared to the single compression, the JPEG down-recompression may change the value of the DCT coefficient by 1, although the modification ratio is small. As a result, the marginal density of the DCT coefficients at each individual frequency and the neighboring joint density will be modified.

Generally forgery manipulation operations including seam carving change the pixels values of original image, and change the original DCT coefficients. As a result, seam carving also modifies the individual frequency-based marginal density and joint density. Therefore, we design the following rich features to detect JPEG down-recompression and seam carving forgery under recompression.

3.4 Large Feature Mining in DCT Domain

3.4.1 Marginal Density

The Quantized DCT coefficient array consisting of $B_1 \times B_2$ blocks. The F_{ij} ($i = 1, 2, \dots, B_1; j = 1, 2, \dots, B_2$)-th block consists of 8×8 quantized DCT coefficients. The coefficient at the frequency coordinate (m, n) of the block F_{ij} ($m=0,1, \dots, 7$, and $n=0,1, \dots, 7$) is denoted by c_{ijmn} . The marginal density of the coefficients is calculated by

$$absM(m, n; x) = \frac{\sum_{i=1}^{B_1} \sum_{j=1}^{B_2} \delta(|c_{ijmn}| = x)}{B_1 B_2} \quad (12)$$

Where $\delta = 1$ if its arguments are satisfied, otherwise $\delta = 0$; x is integers from 0 to 5. The frequency coordinate pair (m, n) is set to $(0,1), (1,0), (2,0), (1,1), (0,2), (0,3), (1,2), (2,1), (3,0), (4,0), (3,1), (2,2), (1,3)$, and $(0,4)$, a subtotal of 84 features.

3.4.2 Neighboring Joint Density on Intra-block

The individual frequency-based neighboring joint density on horizontal direction and vertical direction are given by:

$$absNJ_{1h}(m, n; x, y) = \frac{\sum_{i=1}^{B_1} \sum_{j=1}^{B_2} \delta(|c_{ijmn}| = x, |c_{ijm(n+1)}| = y)}{B_1 B_2} \quad (13)$$

$$absNJ_{1v}(m, n; x, y) = \frac{\sum_{i=1}^{B_1} \sum_{j=1}^{B_2} \delta(|c_{ijmn}| = x, |c_{ij(m+1)n}| = y)}{B_1 B_2} \quad (14)$$

In our detection, the frequency coordinate pair (m, n) is set to $(0,1), (1,0), (2,0), (1,1), (0,2), (0,3), (1,2), (2,1), (3,0), (4,0), (3,1), (2,2), (1,3)$, and $(0,4)$. The integer values x and y are set from 0 to 4. There are a subtotal of 700 features.

3.4.3 Neighboring Joint Density on Inter-block

Similarly, we construct the inter-block neighboring joint density on individual frequency band along the horizontal direction and vertical direction, the features are constructed as follows:

$$absNJ_{2h}(m, n; x, y) = \frac{\sum_{i=1}^{B_1} \sum_{j=1}^{B_2-1} \delta(|c_{ijmn}| = x, |c_{i(j+1)mn}| = y)}{B_1(B_2 - 1)} \quad (15)$$

$$absNJ_{2v}(m, n; x, y) = \frac{\sum_{i=1}^{B_1-1} \sum_{j=1}^{B_2} \delta(|c_{ijmn}| = x, |c_{(i+1)jmn}| = y)}{(B_1 - 1)B_2} \quad (16)$$

The pairs of (m,n) and (x,y) are the same to equations (13) and (14), thus we obtain another 700 features.

3.4.4 Calibrated Feature Mining

The JPEG image under examination is decoded into spatial domain, and it is denoted by matrix $I(i,j)$ ($i=1, 2, \dots, p; j=1, 2, \dots, q$). For $d_1=0$ to 7, and $d_2=0$ to 7, while $(d_1, d_2) \neq (0,0)$, the following steps i) to iii) are processed:

- i. The matrix $I(i,j)$ is shifted by d_1 rows and d_2 columns in the spatial domain, and a shifted spatial image $S'(d_1, d_2)$ is generated, here $I'(d_1, d_2) = I(i-d_1, j-d_2)$ ($i=d_1+1, d_1+2, \dots, p; j=d_2+1, d_2+2, \dots, q$);
- ii. The shifted spatial image $I'(d_1, d_2)$ is encoded to the JPEG format at the same quality factor;
- iii. The marginal density and neighboring joint density features are calculated by equations (12), (13), (14), (15), and (16) respectively, based on the shifted JPEG image.

The offset pair (d_1, d_2) is set from $(0,1), \dots(0,7), (1,0), \dots(1,7), \dots(7,7)$, corresponding to 63 shift-recompressions, and thus, a total of $63 \times (84 + 700 + 700) = 93492$ features produced for calibration. By combining original marginal and joint density features with all shifted calibration features together, a total of $64 \times 1484 = 94976$ features are generated from the DCT domain.

3.5 Large Feature Mining in Spatial Domain

Image intensity change over the image is important information in image analysis and computer vision. The intensity change is described with the x and y derivatives G_x and G_y , and the image gradient is the vector $\nabla G = [G_x, G_y]^T$. In this paper we expand the derivatives along different directions over different distances.

We denote an image of size $p \times q$ by the pixel matrix I ,

$$I = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1q} \\ a_{21} & a_{22} & \dots & a_{2q} \\ \dots & \dots & \dots & \dots \\ a_{p1} & a_{p2} & \dots & a_{pq} \end{bmatrix},$$

The derivative G_{ij} is defined the intensity change along the horizontal distance of i and along the vertical distance of j . The derivative matrix is calculated by

$$M_{G_{ij}} = \begin{bmatrix} a_{11} - a_{(j+1)(i+1)} & a_{12} - a_{(j+1)(i+2)} & \dots & a_{1(q-i)} - a_{(j+1)q} \\ a_{21} - a_{(j+2)(i+1)} & a_{22} - a_{(j+2)(i+2)} & \dots & a_{2(q-i)} - a_{(j+2)q} \\ \dots & \dots & \dots & \dots \\ a_{(p-j)1} - a_{p(i+1)} & a_{(p-j)2} - a_{p(i+2)} & \dots & a_{(p-j)(q-j)} - a_{pq} \end{bmatrix}$$

$$= \begin{bmatrix} G_{ij}(1,1) & G_{ij}(1,2) & \dots & G_{ij}(1, q-i) \\ G_{ij}(2,1) & G_{ij}(2,2) & \dots & G_{ij}(2, q-i) \\ \dots & \dots & \dots & \dots \\ G_{ij}(p-j,1) & G_{ij}(p-j,2) & \dots & G_{ij}(p-j, q-i) \end{bmatrix} \quad (17)$$

Spatial derivative large feature mining contains the marginal density and neighboring joint density.

For computational efficiency and feature reduction, our feature extraction is based on the derivative matrices, the algorithm is described below.

Derivative-based large feature mining algorithm

```
for d=1:max_d
  for i=0:d
    j=d-i;
```

% Marginal density features

% $\delta = 1$ if its arguments are satisfied, otherwise 0

```
    for h=0:max_h
```

$$MF_{ij}(h) = \frac{\sum_{r=1}^{p-j} \sum_{c=1}^{q-i} \delta(|G_{ij}(r, c)| = h)}{(p-j)(q-i)} \quad (18)$$

```
    End
```

% Joint density features

```
    for k=0:max_k
      for l=0:max_l
```

$$NJH_{ij}(k, l) = \frac{\sum_{r=1}^{p-j} \sum_{c=1}^{q-i-1} \delta(|G_{ij}(r, c)| = k \ \& \ |G_{ij}(r, c+1)| = l)}{(p-j)(q-i-1)} \quad (19)$$

$$NV_{ij}(k, l) = \frac{\sum_{r=1}^{p-j-1} \sum_{c=1}^{q-i} \delta(|G_{ij}(r, c)| = k \ \& \ |G_{ij}(r+1, c)| = l)}{(p-j-1)(q-i)} \quad (20)$$

```
    end
```

```
  end
```

```
end
```

```
end
```

In our study, we set the values of 8, 10, 10, and 10 to max_d , max_h , max_k and max_l , respectively. The optimal configuration of these parameters could be further explored in the future study. We obtain 484 marginal density features, and 10,648 joint density features, in a sub-total of 11,132 features.

Additionally, image filtering is applied to the image under examination, the filtered version is

obtained. By applying the feature extraction algorithm to the filtered version, another 11,132 features are obtained. We simply utilized image median filtering that could be further investigated. In summary, we extract 22,264 dimensional derivative features.

As we know, the optimal seams are examined by the least importance based on the energy function. We surmise that the seam carving operation changes the statistics of importance distribution. Therefore, we design the following energy statistical features.

For the image $I = \{ a_{ij} \}$ ($i=1, 2 \dots p; j=1, 2 \dots q$), and the parameters f_1 and f_2 are set by $= 1, 2, 3$, respectively. The sub set $I(f_1, f_2, d_1, d_2) = \{ a_{ij} \}$ ($i=f_1+d_1+1, f_1+d_1+2, \dots, f_1+d_1+p-\max(f_1+d_1); j=f_2+d_2+1, f_2+d_2+2, \dots, f_2+d_2+q-\max(f_2+d_2)$). The differential matrices are constructed by:

$$e(d_1, d_2) = \sum_{(f_1, f_2)=(1,1)}^{(3,3)} |I(f_1, f_2, d_1, d_2) - I(2, 2, d_1, d_2)| \quad (21)$$

$$e_1(d_1, d_2) = \min_{f_2=1,2,3} (|I(1, f_2, d_1, d_2) - I(2, 2, d_1, d_2)|) \quad (22)$$

$$e_2(d_1, d_2) = \min_{f_2=1,2,3} (|I(3, f_2, d_1, d_2) - I(2, 2, d_1, d_2)|) \quad (23)$$

$$e_3(d_1, d_2) = \min_{f_1=1,2,3} (|I(f_1, 1, d_1, d_2) - I(2, 2, d_1, d_2)|) \quad (24)$$

$$e_4(d_1, d_2) = \min_{f_1=1,2,3} (|I(f_1, 3, d_1, d_2) - I(2, 2, d_1, d_2)|) \quad (25)$$

We extract the marginal density by

$$absM_e(h) = \frac{\delta(e(0,0)=h)}{(p-2)*(q-2)} \quad (26)$$

The neighboring joint density features are given by

$$absNJ_{e,d}^1(k, l) = \frac{\sum \delta(|e(0,0)|=k, |e(d_1, d_2)|=l)}{(p-d_1-2)(q-d_2-2)} \quad (27)$$

$$absNJ_e^2(k,l)=\frac{\sum \delta(|e_1(0,0)|=k,|e_2(0,0)|=l)}{(p-2)(q-2)} \quad (28)$$

$$absNJ_e^3(k,l)=\frac{\sum \delta(|e_3(0,0)|=k,|e_4(0,0)|=l)}{(p-2)(q-2)} \quad (29)$$

Where $\delta = 1$ if its arguments are satisfied, otherwise $\delta = 0$; the value of h in equation (26) is set from 0 to 10; the integer values of k and l in equations (27) to (29) are set from 0 to 10, there are 121 combinations of (k, l) . In equation (27), the sum of d_1+d_2 is set from 1 to 7, there are 35 combinations of (d_1, d_2) . We obtain a total of 4488 features.

Similarly, image filtering is applied to the image M , the filtered version is obtained. By applying the feature extraction from equations (26) — (29) to the filtered version, another 4488 feature are obtained. In a subtotal, we obtain 8976 energy-based features.

In the DCT domain, we extract $64*(84+700+700) = 94,976$ features, denoted by LF-DCT(large features in DCT transform). By integrating all features from both the spatial domain and the DCT domain together, a total of 126,216 features, denoted by LF-DEDCT (large features on Derivatives, Energy and DCT transform), are generated.

3.6 Ensemble Learning

In machine learning, ensemble methods use multiple models to obtain better predictive performance than could be obtained from any of the constituent models. To cope with high-dimensional predictors in our detection, we adopt the ensemble classifier designed in [14] that makes use of base learners of Fisher Linear Discriminant (FLD). Each FLD-base learner is built on a (uniformly) randomly selected subspace of the feature space as bootstrap aggregating or bagging. All base learners are trained on feature spaces of a dimension that can be chosen to be much smaller than the full dimensionality, which significantly lowers the computational complexity. Even though the performance of individual base learners can be weak, the accuracy quickly improves after fusion and

eventually levels out for a sufficiently large number of base weak learner. The decision threshold of each base learner is adjusted to minimize the total detection error under equal priors on the training set [14]. In the training, a bootstrap sample with roughly 63% of unique samples and the remaining 37% of validation provides a single vote. After all L -base learners are trained, each training sample will collect on average $0.37 \cdot L$ predictions that can be fused using the majority voting strategy into a prediction. Then an unbiased estimate of the testing error known as “out-of-bag” (OOB) estimate is given based on the prediction. The number of based learners, L , is dynamically determined by observing the progress of the OOB estimate. To determine the optimal number of sub feature dimensionality, starting with a small value of sub feature dimensionality, the sub feature dimensionality is kept increasing by a pre-defined step as long as the OOB estimate decreases. Once the OOB error passes its minimum and starts increasing again, then the area at the sub feature dimensionality leading to the lowest OOB error is examined again with refined the step values, until the solution is found within the desired tolerance [14]. The technique details and algorithms are given in the reference [14].

4. EXPERIMENTS

4.1 Detection of JPEG Down Recompression by LF-DCT

4.1.1 Detecting Single Compression and Down-recompression

We obtained 10,000 never compressed raw-format photos by using four digital cameras Nikon D3100, SamSung GX-10, Cannon Rebel EOS T2i, and Olympus PEN E-PL1 (2,500 each from each digital camera). Based on these 10000 never compressed images, we produced 10,000 singly compressed JPEG image at the quality factor of ‘40’ ($QF=40$), 50,000 aligned and 50,000 misaligned JPEG down-compressed image at the second quality factor QF_2 of ‘40’ and the first compression qualities FQ_1 were set to 90, 80, 70, 60, and 50 respectively (10,000 for misaligned and 10,000 for aligned at each first compression quality). The size of each image is 512 by 512. We apply the

ensemble classifier proposed in [14] to the 94,976 dimensional LF-DCT features that were extracted from these 110,000 images. We run 30 experiments to distinguish between single compression and each type of down-recompression. In each experiment, 50% samples from single compression and 50% from the down-recompression are randomly selected for training and the remainders are used for testing. The prediction outcomes of testing sets are classified as True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). The detection accuracy is given by $0.5*TP/(TP+FN)+0.5*TN/(TN+FP)$. Table II shows the mean detection accuracy by comparing proposed approach and three popular and noticeable methods [2, 19, 21] in detecting JPEG double compression including JPEG down-recompression.

The detection results show that our proposed approach is superior to compared methods. Especially in detecting the misaligned JPEG down-recompression, the improvement over the existing method is noticeable. For example, proposed approach obtained between 90% to 99% accuracy in detecting misaligned down-compression wherein the first compression factor is equal to or smaller than 80, while the detection accuracy by using compared method only gained about 60% to 70%.

Table II. Mean Detection Accuracy (%)

Detecting down-recompression ($QF_2 = 40$) and the single compression ($QF=40$).

QF ₁	Detection accuracy							
	Aligned				Non-aligned			
	Proposed	[21]	[19]	[2]	Proposed	[21]	[19]	[2]
50	99.4	99.0	81.6	87.2	99.3	70.2	98.6	54.1
60	99.7	98.8	89.7	73.1	98.4	66.7	96.4	55.1
70	99.9	99.6	94.3	92.4	95.6	63.2	90.9	55.0
80	98.8	95.8	64.7	69.7	90.9	62.5	79.1	54.0
90	97.4	93.5	69.4	64.5	75.7	61.5	66.8	51.8

4.1.2 Detecting First Compression Quality from the Down-recompression

The same experimental process is conducted as described in section 4.1.1. We designed three types of experiments: a) detection of the first compression quality from aligned down-recompression; b) detection of the first compression from aligned down-recompression and misaligned down-

recompression. The misaligned down-recompression was originally compressed at a higher first compression quality factor, compared to the first compression quality of the aligned down-recompression; and c) detection of aligned down-recompression and misaligned down-recompression. The misaligned down-recompression was once compressed at a lower image compression quality. Table III list the mean detection accuracy in recognizing the first compression image quality based on the down-recompressed images.

Table III. Mean Detection Accuracy (%)

Detecting the first compression quality (QF_1) ($QF_2=40$)

$QF_1/$ QF_1	Detection accuracy											
	Aligned vs. Aligned				Non-aligned vs. aligned				Aligned vs. Non-aligned			
	Proposed	[21]	[19]	[2]	Proposed	[21]	[19]	[2]	Proposed	[21]	[19]	[2]
50/60	99.6	99.1	81.4	98.2	99.7	98.7	98.9	72.5	99.2	99.2	96.5	90.8
50/70	99.9	99.9	97.4	98.8	99.9	99.7	99.1	91.5	99.4	99.1	92.3	90.8
50/80	99.4	99.4	81.3	94.8	99.2	96.3	98.7	70.6	99.4	98.9	83.7	90.9
50/90	99.6	99.2	82.6	91.7	99.4	95.0	98.6	67.2	99.5	98.9	79.4	91.5
60/70	99.9	99.9	98.3	99.2	99.8	99.7	98.7	91.2	99.6	98.6	93.8	75.9
60/80	99.7	98.7	89.4	76.2	99.1	96.3	96.5	71.8	99.6	98.2	89.8	73.7
60/90	99.9	98.9	91.2	75.3	99.3	94.7	96.3	67.8	99.7	98.8	89.2	72.0
70/80	99.9	99.7	92.9	94.7	99.2	96.3	90.6	72.1	99.9	99.5	95.8	92.5
70/90	100.0	99.6	96.5	96.8	98.2	94.2	91.9	66.8	100.0	99.4	93.9	91.8
80/90	99.2	96.9	76.8	76.9	97.4	93.3	82.7	66.6	98.8	96.0	68.5	71.0

4.1.3 Detecting Aligned and Misaligned Down-recompression under the Same First Compression

In this type of experiments, we produced 50,000 aligned down-recompression images and 50000 misaligned down-recompression images. The experimental setup and processing are the same, as described in 4.1.1. Table IV lists the mean detection accuracy.

Table IV. Mean Detection Accuracy (%)

Discriminating misaligned from aligned recompression ($QF_2 = 40$) under the same first compression

QF_1	Detection accuracy			
	Proposed	[20]	[18]	[2]
50	99.6	99.1	98.5	91.5

60	99.7	98.6	96.9	75.3
70	99.9	99.5	97.3	92.9
80	99.0	95.9	79.9	72.0
90	97.1	92.8	75.2	67.1

4.1.4 Discriminating Misaligned Down-recompression under the Same First Compression

As we know, there are $63 \times 62 = 3906$ combinations of misalignment pairs, and the computational cost is too high for us to complete all combinations at this moment. To test LF-DCT features for the discrimination of the misalignment, we randomly select the misalignment pairs (1, 0), (2, 0), (7, 6), and (7, 7), and produced 50,000 misaligned down-recompression images ($QF_1=50, 60, 70, 80$, and 90 ; $QF_2=40$) for each of these four misalignments, in a total of 200,000 images. Table V shows the mean testing accuracy in distinguishing these different misalignments. It is clear that the proposed method is superior to the existing method.

Table V. Mean Detection Accuracy (%)

Distinguishing one misalignment from another under the same first image quality (QF_1) ($QF_2 = 40$)

Misalignment vs misalignment		QF_1	Detection accuracy			
			Proposed	[21]	[19]	[2]
(1,0)	(2,0)	50	99.5	92.4	98.7	69.1
		60	99.4	94.8	97.6	60.9
		70	99.1	73.9	95.4	58.5
		80	94.9	61.2	78.1	54.5
		90	79.5	56.4	64.4	52.5
(1,0)	(7,6)	50	99.4	91.3	99.5	65.7
		60	99.4	94.7	98.7	60.5
		70	98.9	73.2	96.0	54.5
		80	93.4	62.5	79.5	51.6
		90	76.7	54.4	64.9	51.2
(1,0)	(7,7)	50	99.5	98.2	99.4	64.6
		60	99.5	95.9	98.9	60.8
		70	99.0	71.4	96.7	59.8
		80	92.4	62.3	80.0	52.2
		90	73.6	55.4	65.3	50.8
(2,0)	(7,6)	50	99.4	87.5	99.3	66.2
		60	99.3	82.8	98.1	55.4
		70	98.9	77.7	88.8	56.2
		80	95.1	63.9	78.1	54.4

		90	80.7	55.5	64.4	51.9
(2,0)	(7,7)	50	99.6	90.6	99.3	58.1
		60	99.2	82.0	98.1	56.4
		70	98.2	76.3	91.5	59.2
		80	95.5	62.3	77.6	53.3
		90	79.9	57.5	64.6	51.1
(7,6)	(7,7)	50	98.4	70.2	98.1	59.4
		60	98.0	67.6	95.6	55.7
		70	97.1	60.4	92.0	55.9
		80	94.6	59.9	83.6	53.4
		90	82.4	54.7	72.5	51.5

4.1.5 Detecting Down-recompression with Down-rescaling

To evade from being detected, the modified image may be resampled before the second JPEG compression. Regarding JPEG recompression with the image rescaling, we proposed a method to detect the integration of JPEG rescaling followed by the recompression with the same quantization table [19], wherein different interpolation methods were examined including nearest-neighboring interpolation, bilinear interpolation, cubic interpolation, interpolation with a box-shaped kernel, interpolation with a Lanczos-2 kernel and interpolation with a Lanczos-3 kernel. Our previous study shows that different interpolation methods may lead to a slight different detection performance, but the detection performance mainly depends on the scaling factor, not on the different interpolation methods. Generally, the detection of up-scaling (scaling factor is larger than 1) is much better than the detection of down-scaling (scaling factor is smaller than 1). Bianchi and Piva [3] designed a method to detect JPEG double compression with image rescaling. Their implementation is based on the detection of JPEG recompression with nearest-neighboring interpolation. To compare these two detection methods, we selected 2500 never compressed images, and compressed these images to the quality from 40 to 90 with the step of 10, respectively. Then, the singly compressed images with the qualities of 50 to 90 are rescaled by using nearest-neighboring interpolation at the scale factors of 0.6, 0.7, 0.8, and 0.9, respectively. Finally these rescaled JPEG images are saved at the lower quality of 40. The detection is to distinguish these down-scaling and down-recompressed images from the

single JPEG compression at the quality of 40 (generally the detection of down-scaling is more challenging than the detection of up-scaling). Table VI lists the mean detection accuracy over 30 experiments by using these three detection methods. The results demonstrate our significant improvement over compared methods.

Table VI. Mean Detection Accuracy (%)

Detecting down-scaling and down-recompression ($QF_2 = 40$)

QF_1	scale	Detection accuracy		
		Proposed	[21]	[3]
50	0.6	95.8	79.8	54.9
	0.7	76.6	64.7	54.0
	0.8	98.1	94.3	51.9
	0.9	90.9	61.2	52.1
60	0.6	95.1	79.2	54.9
	0.7	74.8	64.8	53.7
	0.8	98.1	94.3	50.2
	0.9	89.8	62.0	51.6
70	0.6	95.0	78.9	55.0
	0.7	73.7	64.6	53.9
	0.8	97.9	94.2	50.5
	0.9	87.5	60.1	52.1
80	0.6	94.9	78.2	55.3
	0.7	74.0	64.6	54.3
	0.8	97.9	94.4	49.7
	0.9	87.1	59.8	52.1
90	0.6	94.8	78.8	54.4
	0.7	74.5	64.4	52.6
	0.8	97.8	94.2	50.5
	0.9	85.2	60.0	52.5

4.2 Detection of Seam Carving under Recompression

We have 3600 JPEG color images, encoded at the quality of ‘75’. The seam carving tool at <http://code.google.com/p/seam-carving-gui/> is used to manipulate these JPEG images due to the good manipulation performance after several seam carving tools were tested. Doctored images are stored in JPEG at the same quality ‘75’. Untouched 3600 JPEG images are also uncompressed and stored at the same quality ‘75’. Some untouched images and doctored at quality ‘75’ are shown in

Figure 4. Then both untouched and doctored images are transcoded to the quality of '40'. The task is set to discriminate the doctored images of quality '40' from the untouched of quality '40'.

Figure 4. Examples of untouched images (odd rows) and doctored images (even rows) at the quality of ‘75’

We compare our detectors LF-DCT and LF-SEDCT to other detectors within the state-of-the-art, including cc-absNJ in the reference [22], the detectors designed in the references [4, 27, 32, 33], and the forgery detection method designed in [31] for detecting color image forgery, including the detectors Markov-Y/Cr/Cb and the combination Markov-YCrCb. Ensemble learning [14] that was designed for image steganalysis to deal with large scale features and to avoid overfitting is applied to our proposed detectors.

Table VII lists the mean accuracy over 30 experiments by applying the ensemble classifier in detecting untouched JPEG images (quality of ‘40’) and doctored JPEG images (quality of ‘40’). In each experiment, 67% observations are randomly selected for training and other 33% observations are used for testing. The prediction outcomes of testing sets are classified as True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). The detection accuracy is given by $0.5 \cdot TP / (TP + FN) + 0.5 \cdot TN / (TN + FP)$. Compared to the existing neighboring joint density feature set, cc-absNJ, the integration of spatial differential neighboring joint density and DCT domain-based marginal and neighboring joint density improve the detection accuracy by about 20%; compared to other methods, the detection accuracy is improved by about 40%.

Table VII. Mean Detection Accuracy (%)

Detecting seam carving forgery under recompression ($QF_1 = 75$; $QF_2 = 40$)

Feature set or detection method	Detection accuracy (%)
Markov-Y [31]	51.1
Markov-Cr [31]	53.1
Markov-Cb [31]	53.1
Markov-YCrCb [31]	54.4
Chang et al. 2013 [4]	53.5
Yin et al. 2015 [33]	51.9
Wei et al. 2014 [32]	51.8
Ryu and Lee 2014 [27]	56.4
cc-absNJ [22]	74.5

LF-DCT	89.8
LF-DEDCT	94.1

Additionally, we test the classification accuracy in detecting the seam carving forgery under the recompression on the same quality of 75. Table VIII lists the mean detection accuracy. It also demonstrates the significant improvement in terms of the detection accuracy by proposed approach.

Table VIII. Mean Detection Accuracy (%)

Detecting seam carving forgery under recompression ($QF_1 = 75$; $QF_2 = 75$)

Feature set or detection method	Detection accuracy (%)
Markov-Y [31]	52.7
Markov-Cr [31]	56.3
Markov-Cb [31]	56.5
Markov-YCrCb [31]	62.2
Chang et al. 2013 [4]	63.9
Yin et al. 2015 [33]	55.4
Wei et al. 2014 [32]	51.9
Ryu and Lee 2014 [27]	64.4
cc-absNJ [22]	93.0
LF-DCT	94.4
LF-DEDCT	99.3

4.3 Discussions

Based on our previous study, we proposed a large-scale feature mining-based approach to detecting JPEG down-recompression and seam carving forgery under recompression anti-forensics. Experimental results show that proposed approach significantly improved the detection accuracy.

To analyze the effective of each individual feature, we performed a paired t-test of the hypothesis that two types of matched samples: 1) untouched recompression JPEG images (initial JPEG compression quality of ‘75’ and second compression quality of ‘40’); and 2) seam carving recompression JPEG

images (initial compression at quality of ‘75’, followed by seam carving, and recompression at quality of ‘40’). Then we test each individual feature with the null hypothesis that these two types of matched samples come from distributions with equal means. The p-value gives the probability of observing the given matched samples with the equal mean. Small p-values doubt on the validity of the null hypothesis. Figure 5 shows the occurrences of the p-values of our features, wherein most individual features show that the matched samples are of different means, indicating the effectiveness of our proposed approach.

Figure 5. The occurrence of the p-values of our features in detecting seam-carving forgery under low quality recompression

In our future study, more reasonable features will be explored. Meanwhile, similar to our previous study in image and audio steganalysis [15, 18, 20], feature evaluation and feature selection will be carried out. Additionally, image texture analyses [15, 25], and the seam carving classification models under different image textures will be explored.

5. CONCLUSIONS

To address the problems of detecting JPEG down-recompression and detecting seam carving-based forgery under JPEG recompression anti-forensics, we first analyze the statistical modification to the DCT coefficients by JPEG down-recompression, and design large-scale feature mining-based approach

to the detection. Ensemble classifier is applied to the rich features for the detection. Experimental results show that our approach redefines the state of detecting JPEG down-recompression and it also effectively detects the seam carving forgery under recompression anti-forensics, which was not well explored before.

Our following study indicates that by integrating spatial-domain feature mining with the proposed DCT-domain rich feature mining together, we may also successfully solve other image forensics problems that were not well exposed before. In addition to design new spatial-domain-based features, feature evaluation and feature selection will be carried out in our future study.

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