Double JPEG Compression Detection Based on Fusion Features

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Abstract. Detection of double JPEG compression plays an increasingly important role in image forensics. This paper mainly focuses on the situation where the images are aligned double JPEG compressed with two different quantization tables. We propose a new detection method based on the fusion features of Benford features and likelihood probability ratio features in this paper. We believe that with the help of likelihood probability ratio features, our fusion features can expose more artifacts left by double JPEG compression, which lead to a better performance. Comparative experiments have been carried out in our paper, and experimental result shows our method outperforms the baseline methods, even when one of the quality factors is pretty high.

Keywords: Double compression detection · DCT coefficients
Likelihood probability ratio features · Benford features

1 Introduction

With the development of technology and the popularity of the digital image editing softwares, people can arbitrarily tamper, repair and adjust images with different purposes, which brings significant concern over the integrity of digital images, especially in the field of image forensics. Therefore, how to guarantee the authenticity and reliability of digital images is of great importance. As a digital image compression standard, JPEG is now widely used in digital cameras. Considering the essential positions of JPEG compression in image capturing and processing, the JPEG image forensic has been attracting more and more attention recently. In this paper, we focus on the research of double JPEG compression detection.

According to whether the two compressed blocks are aligned, double JPEG compression can be divided into aligned double JPEG compression (A-DJPG) and non aligned double JPEG compression (NA-DJPG). This paper considers the case of aligned double JPEG compression with two different quantization tables. Now there are already numerous methods to detect aligned double JPEG compression with different quantization tables. Fu *et al.* [1] noted that the first

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digit of the DCT coefficients follows the Benford's law and the characteristics of the image will be destroyed after compression. Li *et al.* [2] made an improvement on this basis, and proposed a special model to measure the first digital distribution. Feng and Doerr [3] observed the periodicity and discontinuity contained in the double compressed JPEG images and extracted these features from the pixel histograms to detect the aligned double JPEG compression. Popescu and Farid [4] and Popescu [5] had experimentally found that double JPEG compressed images show periodic characteristic on JPEG coefficients, which can be considered as a clue to distinguish single compressed images from double compressed images.

After further analysis of double JPEG compression, Ramesh *et al.* [6] found that the JPEG coefficients histograms would show a double peak obviously when the two JPEG compression quantization tables are different. Lukáŝ and Fridrich [7] extracted the features according to this phenomenon for double JPEG detection. However, since the high frequency components of the JPEG coefficients have a large number of zeros, the algorithm only extracts the histogram features from the nine positions in the low frequency AC coefficients, which includes 144-D features. Chen *et al.* [8] calculated the difference matrix of the JPEG coefficients in four directions, and then extracted features from the Markov transition probability of the difference matrix. In their work, a total of 243-D Markov features were extracted and a decent detection result of double JPEG compression was achieved. A recent work is [9], Shang *et al.* improved the traditional first-order Markov transition probability algorithm and proposed a method based on content analysis and high order statistic features, which obtain a higher detection accuracy. It is worth mentioning that double JPEG compression with the same quantization matrix can also be detected nowadays [10], but this situation is not within the scope of this study.

In this paper, we propose a double JPEG compression detection method based on the fusion features of Benford features and likelihood probability ratio features. The likelihood probability ratio features are based on the distribution of the DCT coefficient, which show the probability of each image block of being doubly compressed, and the Benford features are based on the digital statistical properties of the DCT coefficients. We believe that the combination of this two kinds of features can expose more artifacts left by double JPEG compression, and therefore lead to a better performance.

The rest of this paper is organized as follows. In Sect. 2, we give a brief review of the process of single and double JPEG compression and model the DCT coefficients after double compression. In Sect. 3, we introduce how to extract the two kinds of features used in our experiments in detail. And several comparative experiments are carried out in Sect. 4 to show the effectiveness of our proposed method. Conclusions are drawn in Sect. 5.

2 Aligned Double JPEG Compression

In this section, we briefly review the process of JPEG compression and introduce the statistical model used to characterize A-DJPG artifacts.

2.1 The Process of JPEG Compression

JPEG, Joint Photographic Experts Group, is a widely used image compression standard for grayscale images and color images. JPEG compression can be divided into lossy compression and lossless compression. Where lossless compression means that the decompressed image is the same as the original image in a single scan, and lossy compression generally uses a DCT transform and obtain a JPEG image with higher compression rate based on the Huffman encoding. The JPEG image has high compression ratio and small memory, which makes it widely used in digital cameras. The JPEG image compression can be modeled by four basic steps: the conversion of color space, 8×8 sub-block DCT transformation of the image pixels, quantization of DCT coefficients according to a certain quantization table, and encoding of the quantized values. The process of decompression of JPEG images is just the opposite of the above process. First, the JPEG compressed image is decoded according to the coding table, and then the image of YCbCr mode is obtained by inverse quantization and inverse DCT transformation. The image is transformed into a true color image of RGB mode at last. We generally consider that quantization is achieved by dividing each DCT coefficient by a proper quantization step Q and rounding the result to the nearest integer, whereas inverse quantization is achieved by simply multiplying by Q. This process can be modeled as follows:

$$D_i = \left\lfloor \left\lfloor \frac{d_i}{Q} \right\rfloor Q \right\rfloor \tag{1}$$

where d_i denotes the DCT coefficients of the original image, D_i is the DCT coefficients after inverse quantization, and Q is the quantization step used for JPEG compression. Since the quantized DCT coefficients are obtained by rounding, it is only the approximate value of the original value. We can not recover the original DCT coefficients accurately.

2.2 The Process of Aligned Double JPEG Compression

This paper considers the case of aligned double JPEG compression with two different quantization tables. Given an uncompressed image I, the single compressed image I_1 is obtained by compression of image I with quality factor Q_1. Then I_1 is decompressed, and compressed again by another quality factor $Q2$, where the corresponding block DCT is perfectly aligned. The DCT coefficients after double compression can be modeled as:

$$C_2 = Q_2\left(D_{00}I_1\right) = Q_2\left(D_1\left(Q_1\left(U\right)\right) + D_{00}E_1\right) \tag{2}$$

where $U = D_{00}I$ are the unquantized DCT coefficients of I, Q_1 and Q_2 denotes different quantization tables used in compression, and E_1 is the error introduced by rounding and truncating.

3 Proposed Method

Based on the above analysis, we propose a detection method for double JPEG compression based on the fusion features in this section, which consist of Ben-Ford features and likelihood probability ratio features. The block diagram of our method is shown in Fig. 1. The method mainly consists of three parts: DCT coefficients calculation, fusion features extraction and classification. Firstly, the DCT coefficients are calculated from the given images, and then the likelihood probability ratio features and the Benford feature are extracted. The two features are fused into a SVM classifier to train a model to detect double JPEG compression. In the following, we will introduce the features used and their extraction methods in detail.

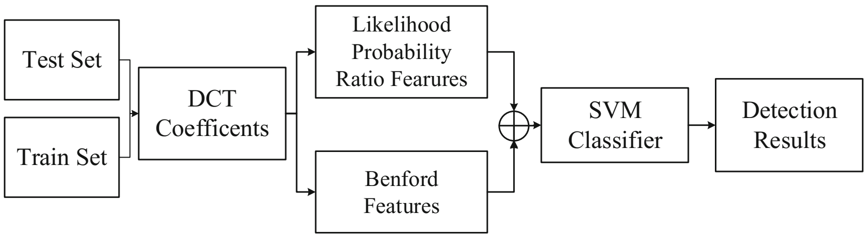

Fig. 1. The block diagram of the proposed method.

3.1 Benford Features

The fusion features consist of two parts: Benford features and likelihood probability ratio features. First, Benford law is a well-known natural statistical phenomenon, it is mainly used to count the frequency of occurrence of natural numbers from 1 to 9 and can be expressed as:

$$P\left(d\right) = \log_{10}\left(1 + \frac{1}{d}\right) \tag{3}$$

where $P(d)$ is the probability of the occurrence of the number d. The distribution of digital statistics follows an interesting law called Benford Law, where the frequency of 1 appears about one-third, and the probability of occurrence of $2, 3, 4, \ldots, 9$ decreases in turn.

Fu *et al.* [1] found that the first digit of the JPEG image before the quantization of the DCT coefficients follow the Benford rule. For a JPEG compressed image, the first digital distribution of the quantized DCT coefficients do not follow the Benford rule strictly, while the first digital distribution of the DCT coefficients is similar to the logarithmic distribution of the Benford rule. They referred to this phenomenon as generalized Benford distribution, which can be expressed as follows:

$$P\left(x\right) = N\log_{10}\left(1 + \frac{1}{s + x^{q}}\right), x = 1, 2, \ldots, 9 \tag{4}$$

where N is the normalization parameter, s and q is the parameters of Benford rule model that changes with the JPEG compression quality factor. For a double JPEG compressed image, the first digit of the DCT coefficients will no longer satisfy the generalized Benford distribution. Based on the difference of distribution, Fu *et al.* [1] took the first digital distribution of the DCT coefficients as features to detect double JPEG compression. Amerini *et al.* [11] used Benford features to detect whether an image is locally compressed. In this paper, the Benford feature vector from [11] is used.

3.2 Likelihood Probability Ratio Features

The likelihood probability ratio features are based on the variation of the DCT coefficients distribution. Bianchi and Piva [12] proposed likelihood probability ratio to generate likelihood map to detect image forgery localization. The ratio shows the probability of each image block of being doubly compressed, which can be used in double JPEG compression detection. Assuming I is an uncompressed image, I_1 is a single JPEG compressed image with quality factor Q_1, then I_1 can be expressed as follows:

$$I_1 = D_{00}^{-1} D \left(Q \left(D_{00} I \right) \right) + E_1 = I + R_1 \tag{5}$$

where Q_{00} represents the DCT transform of 8×8 block in the upper left corner, $Q(\bullet)$ and $D(\bullet)$ represents the quantization and inverse quantization respectively, E_1 is the error introduced by rounding and truncation, and R_1 is the total error in the whole JPEG compression process.

When image I_1 is compressed again with another quality factor Q_2, we can get a double JPEG compressed image. The DCT coefficients after double compression can be modeled as:

$$C_2 = Q_2 \left(D_{00} I_1 \right) = Q_2 \left(D_1 \left(Q_1 \left(U \right) \right) + D_{00} E_1 \right) \tag{6}$$

where $U = D_{00} I$ are the unquantized DCT coefficients of image I, Q_1 and Q_2 denote the different quantization tables used in the process of double JPEG compression. Since JPEG compression tables contain 64 quantization steps, the above formula Eq. (6) can be expressed as follows:

$$p_{DQ} \left(x; q_1, q_2 \right) = \sum_{\nu = q_2 x - q_2/2}^{q_2 x + q_2/2} p_1 \left(\nu; q_1 \right) * g_{DQ} \left(\nu \right) \tag{7}$$

where q_1 and q_2 are the first and second quantization steps respectively, $g_{DQ}\left(\nu\right)$ is the rounding and truncation error in DCT domain, and $*$ means convolution. And the following formula models the distribution of the DCT coefficients after quantization and inverse quantization by Q_1:

$$p_1 \left(\nu; q_1 \right) = \begin{cases} \sum\limits_{\mu = \nu - q_1/2}^{\nu + q_1/2} p_0 \left(\mu \right) & \nu = k q_1 \\ 0 & elsewhere \end{cases} \tag{8}$$

where $p_0(\mu)$ represents the distribution of the unquantized coefficients. The rounding and truncation error in the spatial domain is a independent and identically distributed random variable. According to the central-limit theorem, satisfies the Gaussian distribution as shown in Eq. (9):

$$g_{DQ}(\nu) = \frac{1}{\sigma_e\sqrt{2\pi}} e^{-(\nu-\mu_e)^2/\sigma_e^2} \tag{9}$$

If the JPEG image is not double compressed, the Eq. (7) shall be expressed as follows:

$$p_{NDQ}(x;q_2) = \sum_{\nu=q_2x-q_2/2}^{q_2x+q_2/2} p_{0(\nu)} \tag{10}$$

Now, given an image I, if x is the pixel value of I in spatial domain, then its conditional assumption probability distribution can be expressed as follows respectively:

$$\begin{cases} p(x|H_0) = p_{NDQ}(x;q_2) \\ p(x|H_1) = p_{DQ}(x;q_1,q_2) \end{cases} \tag{11}$$

where $p(x|H_0)$ and $p(x|H_1)$ denotes the probability distributions of x conditional to the hypothesis of being singly and doubly compressed. Thus, the likelihood ratio can be obtained as : $\Gamma(x) = p(x|H_1)/p(x|H_0)$. And if the likelihood ratio is greater than 1, then x is double-compressed, otherwise it is not.

4 Experiments and Results

4.1 Image Database

To prove the effectiveness of our proposed method, we carried our experiments on a public database BOSSBase [13], which consists of 10,000 uncompressed grayscale images with size of 512 × 512. We randomly select 500 images to conduct our experiment, some of the image samples used in the experiment are shown in Fig. 2.

These images are firstly compressed into JPEG images with quality factor Q1 vary from 50 to 95 with a step of 5. Thus we get 5000 single compressed images. Then these 5000 single compressed images are compressed again with quality factor Q2 = $50, 55, 60 \ldots, 95$, respectively, to form the set of double JPEG compressed images.

We randomly select 300 images with quality factor Q1 of single compressed images and 300 double compressed images with quality factor Q1 followed by quality factor Q2 to form the training set, and the remaining 200 images of the single and double compressed images are aggregated into testing set. In our experiment, we only consider the situation when Q1 $\neq$ Q2. In this way, we can get 90 groups of training and testing sets.

Fig. 2. Six image samples in BOSSBase dataset.

4.2 Performance Evaluation

To have a fair comparison, Benford method [11], GLDH method [14], and our proposed method are carried out with the same database and experimental environment mentioned above. The experimental results are listed in tables below.

Table 1 shows the result of GLDH method. We can see that the detection accuracy is pretty high nearly 100% when $Q_2 > Q_1$, and the accuracy is higher than 99.25% in most case when $Q_2 < Q_1$, except for some special case when $Q_1 = 50, Q_2 = 55$ or $Q_1 = 55, Q_2 = 50$.

Table 1. Detection results based on GLDH features [14].

Q_1	Q_2									
	50	55	60	65	70	75	80	85	90	95
50	–	50	100	100	100	100	100	100	100	100
55	69	–	99.5	100	100	100	100	100	100	100
60	100	95.25	–	99.5	100	100	100	100	100	100
65	100	100	99.25	–	97.75	100	100	100	100	100
70	100	100	99.5	97.25	–	100	100	100	100	100
75	97	99.5	100	100	99.5	–	100	100	100	100
80	99.5	99.25	96.75	100	100	97.25	–	100	100	100
85	97.25	94.5	99.75	99.25	98.5	100	98.5	–	100	100
90	99	99.75	97.25	96.75	99	99.75	95.75	99.25	–	100
95	99.75	99.75	99.75	99	98.75	99	99.25	96	99.25	–

Table 2. Detection results based on Benford features [11].

Q_1	Q_2									
	50	55	60	65	70	75	80	85	90	95
50	–	100	100	100	100	98.25	100	99.25	99.25	98
55	100	–	100	100	100	100	100	99.25	78.75	95.25
60	100	99.5	-	100	100	100	97.25	98.5	97.25	95.75
65	100	100	100	–	100	100	100	100	100	97.75
70	100	100	100	100	–	100	100	100	99.75	99.5
75	100	100	100	100	100	–	100	100	100	97.75
80	99.75	100	100	100	100	100	–	100	99.75	99.5
85	100	100	100	100	100	100	100	–	100	100
90	100	100	100	100	100	100	100	100	–	99.5
95	100	100	100	100	100	100	100	100	100	–

Table 3. Detection results based on fusion features.

Q_1	Q_2									
	50	55	60	65	70	75	80	85	90	95
50	–	100	100	100	100	100	100	99.75	100	100
55	100	–	99.5	100	100	100	100	99.25	100	99.75
60	100	99.75	–	100	100	100	99.75	100	100	100
65	100	100	100	–	100	99.75	100	100	100	100
70	100	100	100	100	–	100	100	100	100	100
75	100	100	100	100	100	–	100	100	100	100
80	100	100	99.75	100	99.75	100	–	100	100	100
85	100	100	100	100	100	100	100	–	99.5	100
90	100	100	100	100	100	100	100	100	–	100
95	100	100	100	100	100	100	100	99.5	100	–

Also, to prove the effectiveness of our fusion features, the detection accuracy of Benford feature alone is listed in Table 2. Contrary to Table 1, the method performs quite well when $Q_2 < Q_1$, but when Q_2 is higher, the detection accuracy decreases a little bit. The reason is that when the images are recompressed with a higher quality factor Q_2, the artifact left by double compression is much more difficult to track by Benford features.

Table 3 shows the detection results of our proposed method, which outperforms that of work [11,14]. The detection accuracy is 100% in most case, and most others higher than 99.75%. The lowest detection accuracy is 99.25% when $Q_1 = 60, Q_2 = 80$. Figure 3 shows the detection results of the three methods with different Q_1 when $Q_2 = 95$, while Fig. 4 shows the detection results of the three

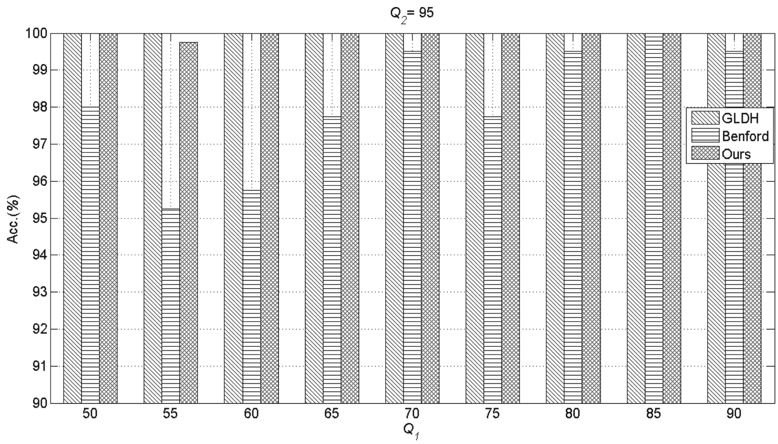

Fig. 3. Detection accuracy with different Q_1 when $Q_2 = 95$.

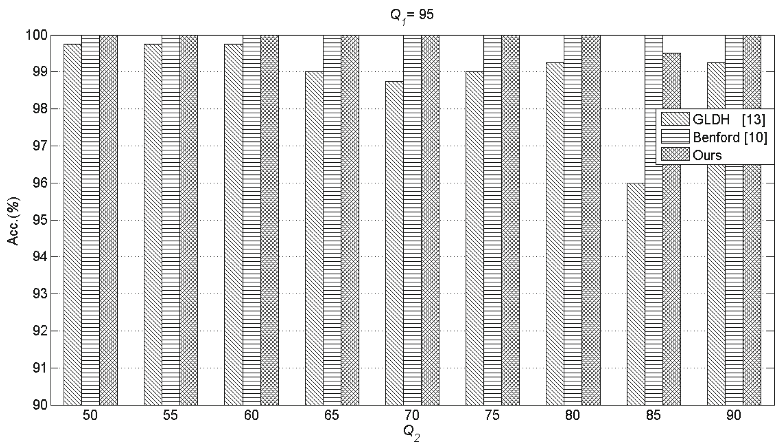

Fig. 4. Detection accuracy with different Q_2 when $Q_1 = 95$.

methods with different Q_2 when $Q_1 = 95$. It is quite obvious that the method proposed in this paper outperforms the baselines, Benford based [11] and GLDH based [14] methods.

5 Conclusion

In this paper, a set of effective fusion features combined Benford features and likelihood probability ratio features are proposed to detect double JPEG compression. Likelihood probability ratio features show the probability of each image block of being doubly compressed, and thus our fusion features can expose more artifacts left by double JPEG compression and therefore lead to a better performance. Comparative experiments show that our method outperforms that of work [11,14], even when the first quality factor or the second quality factor is pretty high.

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