A Robust JPEG Image Tampering Detection Method Using GLCM Features

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Abstract

In this paper, we propose a JPEG image tampering detection method that is robust to post-processing operations such as rotation, resizing, feathering, etc. By finding image blocks that are lack of double compression artifacts, the proposed method can localize the tampered regions. Gray Level Co-occurrence Matrix (GLCM) of the DCT coefficients is used to reveal the double compression artifacts of images. Experiments are designed to show the validity of the proposed method for double compression detection and localization for tampered regions. The proposed method needn't to estimate the first quality factor as most of the previous works do and still works well even when the tampered images are recompressed at a low quality factor.

Keywords: *Robust Tampering Detection, Double JPEG Compression Artifacts, GLCM Features*

1. Introduction

With the popularity of digital devices with camera function and the development of digital image processing software, Image tampering operation becomes an easy trick for ordinary people. It's difficult to tell a given image is authentic or tampered by the naked eyes, thus raise the issue of digital image forensics. What's more, localization of the tampered regions seems to be more important because it gives straightforward evidence whether the questioned image has been tampered or not and where the tampered regions are. Several methods have been proposed to localize the tampered regions, such as the estimation of the CFA pattern and coefficients [1], the detection of the sensor pattern noise [2], the inspection of the inconsistencies in lighting conditions [3], the detection of the demosaicing artifacts [4], the estimation of local noise level [5], the calculation of DCT and Principal Component Analysis-Eigenvalue Decomposition [6], the estimation of the similarity of image blocks [7], etc.

Besides the methods mentioned above, there is another set of methods proposed specific to JPEG images as they have some special characteristics. In [8], the authors proposed an effective localization method by examining the double quantization effect hidden among the histograms of the DCT coefficients. The authors point out that it doesn't work under heavy compression after image forgery. In [9], a passive way to detect image forgery was proposed by measuring its quality inconsistency based on JPEG blocking artifacts. In [10], the authors also proposed an image forgery detection method by analyzing the double compression features. Both [9] and [10] needs to estimate the initial quantization factor of the image. H.Farid pointed out in [11] that the estimation of initial quantization factor is computationally consuming and prone to some estimation error, so he proposed a simple yet effective method to detect doctored parts in a given image using JPEG ghosts, and this approach is effective when the tampered region is of lower quality than the image into which it was inserted.

In this paper, considering the practical fact that when creating a tampered image, the tampered parts often undergone some post-processing operations, such as resizing, rotation, feathering, etc. to make them fit well for the background, we propose a tampering detection method that is robust to the post-processing operations. Double compression artifacts are considered as the jumping-off point of the proposed method. Gray Level Co-occurrence Matrix (GLCM) of DCT coefficients is used to reflect the double compression artifacts. The proposed method can localize the tampered regions without the need to estimate the initial quantization factor of the image as it does in [9] and [10], and works well under low quality factors. What's more, this method is not confined by the demand that the tampered region should be of lower quality than the image into which it was inserted as stated in [11].

The rest of the paper is organized as follows. In section 2, double compression effects on GLCM of the DCT coefficients are analyzed and then an explicit description of the feature generation algorithm is presented in section 3. Experiment designation and results are given in section 4 to show the effectiveness and robustness of the proposed method. In the last section, a discussion and conclusion are provided.

2. Double compression effects on GLCM of the DCT coefficients

In this section, GLCM is first introduced and then the double compression effects on GLCM of the DCT coefficients are analyzed. From the analysis we can see that GLCM can be used as a reflection of double compression artifacts.

2.1. Gray Level Co-occurrence Matrix

GLCM, which is also called as Gray Level Dependency Matrix, was first introduced by Haralick et.al [12] as "Gray-Tone Spatial-Dependence Matrices" to extract various texture features of images. GLCM is obtained by calculating the relative frequencies of occurrence of two pixel pairs with value *m* and *n*, which are separated by a specific distance and angular. It is an estimation of the second order probability density function of the pixels in a given image, and is usually used to represent the texture information of an image. It has been used in various image processing issues, such as texture recognition [13], watermarking [14] and printer source identification [15].

The calculation equation of GLCM is shown in (1):

$$glcm(m,n) = \sum_{(r,l),(r+dr,l+dl)\in I} \delta\{I(r,l)=m, I(r+dr,l+dl)=n\} \tag{1}$$

Where,

$$\delta\{A=m, B=n\} = \begin{cases} 1, if \;\; A=m \; and \; B=n \\ 0, \qquad\qquad otherwise \end{cases} \tag{2}$$

The magnitude of dr and dl represents the separation between two pixel pairs and the sign of them represents the relative direction of the two pixel pairs, if $dr=1$ and $dl=1$, then the spatial relationship of the two pixel pairs is shown in Figure 1.

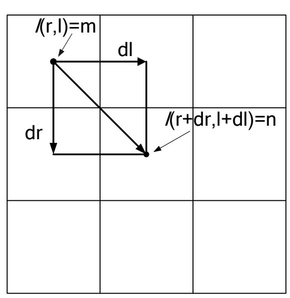

Figure 1. GLCM generation scheme

When calculating the GLCM, the distance of the two pixel pairs are usually set to be 1 and the angular between them are usually 0°, 45°, 90°and 135°and their transpose directions. If the image is isotropic, that is to say the directional information is not required, we can get isotropic GLCM by integration over all the 8 angles and then equation (1) becomes:

$$glcm(m,n) = \sum_{dr=-1}^{1} \sum_{dl=-1}^{1} \delta\{I(r,l) = m, I(r+dr, l+dl) = n\} \tag{3}$$

After the GLCM is calculated, it is usually normalized to represents the probability of occurrence of element pairs with values m and n with separation (dr, dl) and the normalized GLCM is defined as bellow:

$$glcm_N(m,n) = \frac{glcm(m,n)}{\sum_{(r,l),(r+dr,l+dl)\in I} 1} \tag{4}$$

The size of the GLCM depends on the number of different values in the matrix that is considered. If the number of different values is w, then the corresponding GLCM will be a $w \times w$ matrix.

2.2. Double compression effects on GLCM of the DCT coefficients

Double compression artifacts are special characteristics for JPEG images and are mainly caused by the quantization process when the quantization steps of the two compressions are different, as it is a non-invertible operation that causes information loss. The double compression effects on the histogram of DCT coefficients are described in detail in the previous works [8, 10], as is shown in Figure 2 (a) and (b), double compression cause periodical peaks and valleys in the histogram while it is not the case for the single compression situation.

From section2.1, we see that GLCM is mainly used to reflect the texture information of images. From this point of view, we can consider the DCT coefficients matrix as a special image with certain textures and the periodical artifacts on the histogram of DCT coefficients can be viewed as a periodical gray-level fluctuation in the DCT coefficients matrix itself. Shown in Figure 2 (c) and (d) are the distribution of the first row of GLCM for single and double compression respectively. As can be seen, the first row's distribution of GLCM for double compression shows periodical peaks and valleys while it is smooth for the single compression case, so the GLCM can be used as features to reflect the double compression artifacts. In fact, every single row and every single column is a reflection of the double compression artifacts, so by calculating the GLCM instead of using the DCT coefficients matrix directly, the artifacts can be strengthened.

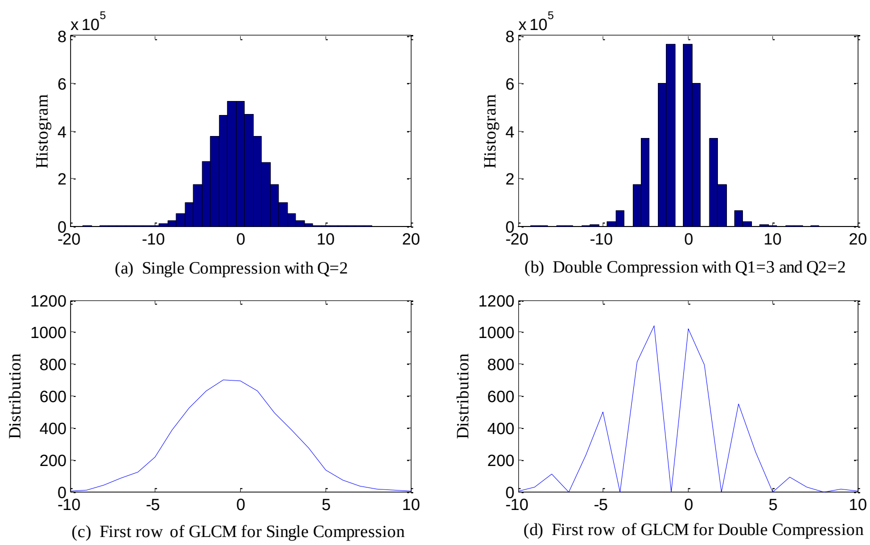

Figure 2. Shown in (a) is the histogram of single compression with quantization step 2. Shown in (b) is the histogram of double compression with quantization step 3 followed by 2. Shown in (c) and (d) are the distribution of the first row of GLCM for single and double compression respectively.

3. Feature generation

After the analysis of double compression effects on GLCM of the DCT coefficients, we give a detailed description of our proposed algorithm in this section. The block diagram of the feature generation scheme is shown in Figure 3.

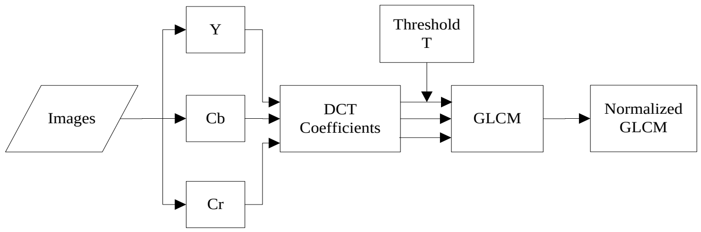

Figure 3. Block diagram of the feature generation scheme

In the proposed method, YCbCr model is used instead of RGB as it is the color model that is adopted by JPEG compression. For a given image, DCT coefficients are first extracted from Y, Cb and Cr channels respectively, and then the isotropic GLCM is calculated based on these DCT coefficients for each channel. Note that a threshold is used here before GLCM is calculated, this is because if we calculate GLCM of DCT coefficients directly, it will result a large size of matrix since the range of DCT coefficient values is broad, which is not desired in practice. Considering that most of the energy of DCT transform is centralized around zero, as is shown in Figure 4, we propose a threshold technique to confine the DCT coefficient values to [-T, +T], thus the size of GLCM will be $(2T+1)\times(2T+1)$. According to the statistical data, T is set to be 4 in our experiment.

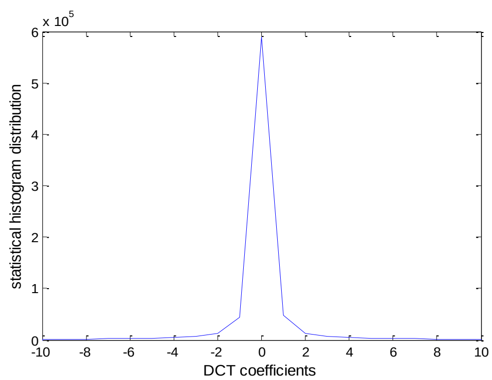

Figure 4. Distribution of the DCT coefficients

At last, the GLCM is normalized. Here, the elements in GLCM is normalized along rows instead of the entire matrix for the consideration that if we normalize the GLCM along the entire matrix, some small values will be forced to zero and cause information loss. The normalization equation of (4) can be rewritten as:

$$glcm_N(m,n) = \frac{glcm(m,n)}{\sum_{(r,l)\in I}\delta\{I(r,l)=m\}} \tag{5}$$

4. Experiment and discussion

In this section, the ability of the proposed method to localize the tampered region in a JPEG image is verified and its robustness to image post-processing and JPEG compression is testified. But before that, we will show the efficiency of the proposed method for double compression detection.

4.1. Double compression detection

This experiment is designed to show the effectiveness of the proposed method in detecting double compressed images. In this experiment, 500 TIF images taken by Kodak DC290 are collected, which include indoor and outdoor scenes with resolution of 720×480. These images are first JPEG compressed using quality Q_1=50, 55, 60… 95 respectively. Then for each set of single compressed images, they are recompressed using qualityQ_1=50, 55, 60…95 respectively. By this way, 100 groups of images are obtained, with each group including 500 single compressed images with quality Q_1 and 500 double compressed images with quality Q_1 followed by Q_2.

Support Vector Machine (SVM) [16] is used as the classifier here. For each group of images, 300 images are randomly selected for training and the left 200 images for testing. The detection results are shown in Table 1. Note that the accuracies are averaged over 20 random experiments.

Comparison is made with work [17] to show the efficiency of our proposed method. The algorithm of [17] is based on the probability distributions of the first digits of the DCT coefficients, which is a first order statistical model. The same database and experimental environment are used and the detection results are shown in Table 2 for comparison.

Table 1. Detection results of the proposed method (by %)

Q_1 \ Q_2	**50**	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**
50	-	98.9	99.9	99.9	99.7	100	100	100	99.9	100
55	93.9	-	98.8	99.6	99.8	100	100	100	99.9	100
60	99.9	97.6	-	98.1	100	100	99.9	100	100	100
65	100	99.9	96.9	-	99.2	100	99.8	100	99.9	100
70	99.9	99.9	100	99.2	-	99.9	100	100	100	100
75	98.3	99.9	100	100	99.8	-	99.8	100	99.9	100
80	99.1	98.6	97.7	100	99.9	99.4	-	99.9	100	100
85	93.6	71.6	97.1	99.4	98.2	99.9	99.7	-	100	100
90	71	91	82.8	98.6	95.5	99.3	98.4	99.9	-	100
95	49.8	50	50.2	50.8	72.2	66.8	90	76.9	99.4	-

Table 2. Detection results of work [17] (by %)

Q_1 \ Q_2	**50**	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**
50	-	97.2	99.7	100	99.9	100	100	100	100	100
55	92.9	-	97.7	99.4	100	99.9	99.8	100	100	100
60	98.5	97.7	-	96.8	99.9	99.9	99.9	100	100	100
65	96	99.9	95.1	-	99.8	99.9	99.9	100	100	100
70	97.9	96.7	99.8	98.4	-	99.8	99.8	99.9	100	100
75	83	95.7	98.4	99	99.4	-	99.5	99.6	100	100
80	96.1	94.5	87.5	99.2	97.4	98.7	-	99.6	99.9	100
85	78.5	66.3	97.2	88.9	92.9	98.8	98	-	99.9	100
90	66	86.2	76.6	98.3	90	96	84.8	98.3	-	100
95	49.6	50	48.8	49.7	57	57.8	70.1	75.8	91.1	-

From the detection results we can see that the ability of the proposed method to detect double compressed image is satisfying except for the situation that Q_1 is as high as 95. And from the comparison shown in Table 1 and Table 2, we see that the accuracy of the proposed method is higher than that of work [17], especially when the second compression quality factor Q_2 is smaller than the first compression quality factor Q_1. This is probably because when$Q_2<Q_1$ the double compression artifacts are not so obvious. But since every single row and column of GLCM is a reflection of the double compression artifacts, the artifacts can be strengthened by our method, thus resulting higher detection accuracy.

4.2 Localization of the tampered images

As is analyzed in [8], a given tampered JPEG image can be divided into two parts: one is the original part that has double compression artifacts, and the other is the tampered part without the artifacts. Several reasons contribute to this phenomenon. Firstly, the tampered part may come from a non-compressed image (e.g. BMP image). Secondly, the blocks of the tampered part may be displaced with the original image which it is inserted to, thus it will be split into four sub-blocks respectively falling into four adjacent blocks and the DCT coefficients are irreversible when computing IDCT before the second compression, of course exhibits no double compression artifacts. What's more, some post-processing such as resizing will also cause the loss of double compression features.

Upon the above analysis, we see that by detecting whether the image blocks have double compression artifacts, the tampered region can be determined. The ability of the proposed method to localize the tampered region in a tampered JPEG image is verified in this section.

4.2.1 Experiment database

Note the fact that most cameras do not use the standard JPEG compression quality factors as those used in the previous section and the quality factors adopted by different cameras are usually different, this experiment is conducted simulating the real situation.

A database of 300 JPEG images is built for training. These images come from different cameras with different resolutions and quantization tables, to name some, Sony a550, Samsung WB550, Canon Eos450D, etc. Then two groups of images are generated from these images. One is obtained by recompressing the images with different quality factors using Adobe Photoshop CS4 (which is popular for image tampering), so it is the group with double compression artifacts. For the other group, the images are first zoomed with 99.5% of the original images to eliminate the first JPEG compression effects, and then JPEG compressed with the same quality factors as the first group, so this group represents tampered regions without double compression artifacts. GLCM Features of the two groups are extracted using the proposed algorithm and a SVM based classifier is trained upon these two sets of features.

4.2.2 Effectiveness Test under Post-processing Operations

For a given test image, it is first divided into overlapped image blocks of size $N\times N$ with step M. To retain the correlations caused by DCT transform, we advise that the size of the image blocks N and step M should be multiple integers of 8 as DCT transform is done upon 8×8 blocks. According to our experiments, a compromise between the accuracy and computational complexity can be achieved if N=128 and M=8. Features are extracted from each image block and the decision whether it is tampered is made by SVM. Some of the detection results are shown in Figure 5.

Listed in the first column are the original images with different resolutions of 1280×960, 4592×3056 and 2048×1536 respectively. Images in the second column are their tampered counterparts. In (b), a girl is inserted into the image. In (e), the head of the person is replaced with another guy's head. In (c), several people are eliminated with the background. The tampered parts have undergone several post-processing techniques to make them fit well with the background. After that, the images are recompressed with quality factor of 12. Shown in the third column are the detection results, those parts marked with black are backgrounds and the white parts represents the tampered regions. From the results we see that the proposed method is effective under different circumstances.

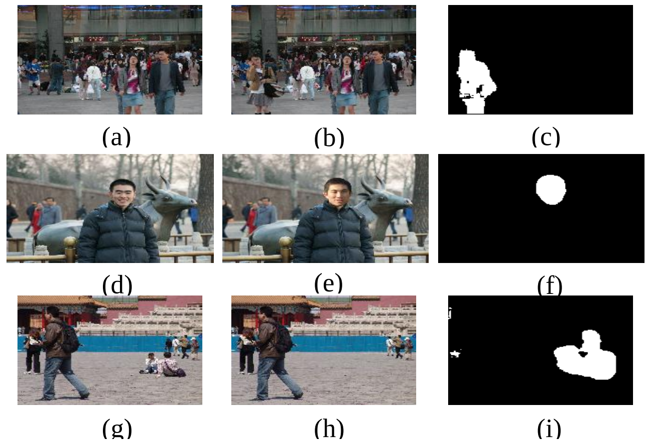

Figure 5. Detection results under different circumstances. Shown in the first column are the original images, images in the second column are their tampered counterparts, these images undergone several post-processing operations after tampering. Shown in the last column are the detection results.

4.2.3 Robustness test to JPEG compression

To testify the robustness of the proposed method to JPEG compression, the tampered images are recompressed at different quality factors and the detection results are shown in Figure 6. The first image is the tampered one which is created by cutting the person from one JPEG image and pasting it to another and then the image is recompressed using different quality factors using Photoshop CS4. From the results we see that the proposed method can detect tampered images compressed at a relatively low quality, but when Q is less than 4, the result is not satisfying. However, since Q=4 is a really low quality factor that is rarely used in practice, our method is robust to most of the situations.

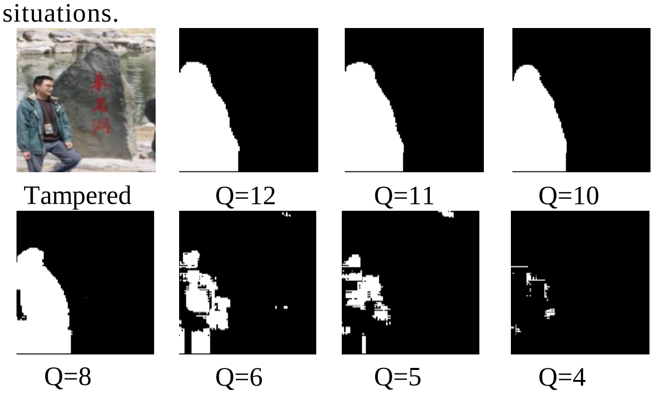

Figure 6. Results of robustness test to JPEG compression.

5. Conclusion

A robust JPEG image tampering detection method is proposed in this paper based on double JPEG compression artifacts. GLCM of DCT coefficients is used to reveal the double compression artifacts. Experiment results show that this method is effective under post-processing operations such as resizing, rotation, feathering, etc. What's more, the method gives promising results even when the tampered images are recompressed at a relatively low quality factor.

Another point to mention is that the choice of image block size N has some influence on the detection result. The smaller the size N, the more precise the localization is for high quality factors, but may fail for low quality factors as the double compression artifacts is not so obvious for small blocks at low quality.

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