Detection of Quantization Artifacts and Its Applications to Transform Encoder Identification

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***Abstract*—Quantization is one of the commonly used techniques in most lossy image source encoders. It is observed that the quantization operation usually introduces some obvious artifacts into the histogram of the corresponding transform coefficients under various compression schemes. By investigating such inherent artifacts over all candidate transform coefficients, it is possible to identify the transform, as well as some parameters previously employed in the transform-based encoder from a decompressed image. In this paper, we first analyze the properties of the quantized coefficients and present a simple yet effective way to detect the quantization artifacts, and then we propose an approach to identify the transform-based encoder based on the quantization artifacts detection. The simulation results evaluated on thousands of natural images with some popular compression schemes demonstrate the effectiveness of our method.**

***Index Terms*—Digital image forensics, quantization artifacts, source encoder identification.**

I. Introduction

DIGITAL images can be easily edited using user-friendly tools such as Photoshop and GIMP. If these tampered images are abused, it may cause many serious problems related to social security and/or legal evidence. Today, authentication of digital images faces many challenges.

Conventional techniques for image authentication need some proactive operations, such as inserting a digital watermark or attaching a digital signature into the host data, and require them to facilitate the authentication. However, in many scenarios, the questionable image does not have such additive information, and therefore, these methods will fail. Recently, passive forensic analysis [1], [2] has attracted much attention. This technique assumes that the previous operations, including various modules and/or the software system in a device, will leave an inherent trace in the resulting image. By analyzing and detecting such inherent patterns, it is possible to identify the operation history of an image. For instance, since different camera models typically employ different quantization tables and/or color filter array (CFA) interpolation algorithms, we can narrow down the possible camera models of a questionable image or further locate the tampered regions by observing the quantization table [3], [4] and estimating specific correlations between pixels [5]. We can also expose JPEG forgeries by detecting the artifacts introduced by double JPEG compression [4], [6], and so on.

In this paper, we focus on the recently proposed problem of source encoder identification [7]–[9], namely, given a digital image without any header information or metadata for previous operations, we wish to identify which transform was used in the source encoder via detecting the quantization artifacts. As mentioned in [7], this has many applications in multimedia security, coding and communication. For instance, it can be used to verify the datapath integrity of an image, and further locate the tampered regions or detect the consistency within an image. Besides, some image enhancement/steganalysis algorithms may rely on the knowledge of image encoders, such as the block sizes, quantization table, decomposition levels. Therefore, source coder identification is a first crucial step for many subsequent analyses, and false identification usually leads to the invalidation of the analysis.

There have been a few relevant approaches [7]–[9] to address the problem of source encoder identification. The main idea of the existing works is to calculate the similarity between the observed histogram of the transform coefficients and the estimated version of the original histogram. The highest value of the similarity measure over the possible candidate encoders indicates the original of the source encoder. There are two problems in these approaches. First, it is difficult to approximate the original histogram from a decompressed image. Second, defining a good and uniform similarity criterion for various source encoders is a difficult task. Therefore, the detection accuracy of the existing works usually decreases significantly as the PSNRs of the test images increase. For instance, in [7], the average accuracy for the source encoder identification is around 90% when the PSNR is less than 36 dB, while it drops to 80% when the PSNR rises to 40 dB. Besides that, the computation complexity is high due to the estimation of the original histogram using nonlinear least-square data fitting. Furthermore, some existing methods, e.g., [8], usually misclassify the Slant transform as the discrete cosine transform (DCT). For block sizes estimation, the average accuracies of the existing approaches [7], [10], [11] are still far from satisfactory when the PSNR is higher than 40 dB and/or the block size is larger than 32×32.

The general transform coding system [12] for the image encoder and decoder is illustrated in Fig. 1. Since quantization

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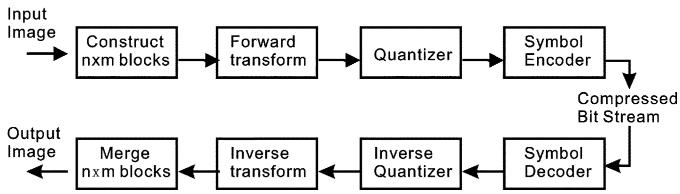
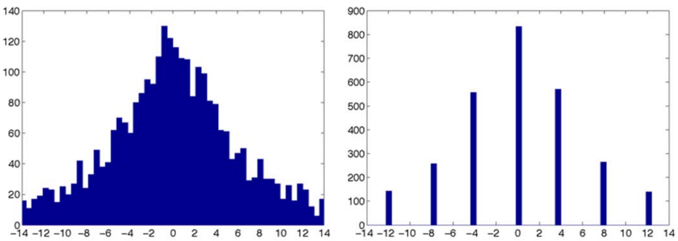


Fig. 1. General transform coding for digital images.



(a) (b)

Fig. 2. Histograms of d_1, d_1' for Lena image with a quality factor 85 at the position (1,1), and the corresponding quantization step 4. (a) Histogram of $d_1(1,1)$. (b) Histogram of $d_1'(1,1)$.

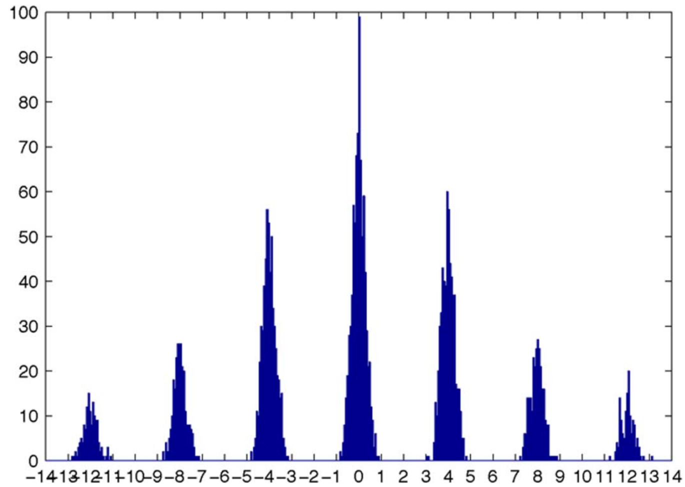


Fig. 3. Histogram of $d_2(1,1)$ after JPEG decompression.

is an effective technique to reduce the number of coefficients required to represent an image via compressing a range of coefficients into a single quantum value, it is widely employed in these transform-based encoders, such as lossy JPEG, JPEG2000, and various sub-band image compression schemes. One of the quantization artifacts is that those transform coefficients with values around zero will usually be quantized to zero, and thus the number of transform coefficients with zero value will increase sharply after quantization, especially when the quantization step is large (see Fig. 2(a) and (b) on JPEG compression). Since different source encoders may employ different transforms (e.g., DCT, DWT, etc.) and/or compression parameters (e.g., block sizes, decomposition levels, etc.), such quantization artifacts will only be obviously presented in the histogram of the corresponding coefficients. By detecting the artifacts over all candidate transforms' outputs, it is possible to identify the original source encoder from a decompressed image. This is the main idea of our proposed scheme, and the key issue is to detect quantization artifacts—the uniform feature for various lossy source encoders.

In this paper, we introduce an effective 2-D feature vector to detect the quantization artifacts (rather than comparing the similarity between the transform coefficients and the estimated version in previous methods), and propose a scheme for identifying the source encoder and/or the corresponding parameters. The experimental results, evaluated on thousands of natural images with some popular compression schemes, show the effectiveness of our method.

The rest of the paper is organized as follows. Section II presents a simple yet effective method for detecting quantization artifacts. Section III proposes our method for image source encoder identification. Section IV demonstrates the experimental results and analysis. The concluding remarks and discussions will be set out in Section V.

II. Detection of Quantization Artifacts

JPEG is one of a number of popular transform-based encoders. In this section, we will take JPEG images as examples and show the properties of the histograms of the ac components before and after quantization operations, and then we present a 2-D feature vector to detect such quantization artifacts.

In JPEG compression, the input image I is first divided into nonoverlapping 8×8 blocks. For each block, the forward DCT is preformed to obtain the DCT coefficients d_1, which are then quantized by a quantization table Q. The quantization coefficients are further compressed using entropy coding. Finally, the resulting bit stream is combined with a file header to generate the JPEG file.

In JPEG decompression, the JPEG file is first entropy decoded to recover the quantized coefficients, which are then multiplied by a quantization table Q to obtain the dequantization coefficients d_1'. Finally, the inverse DCT (IDCT) is applied to d_1' and the results are truncated and rounded to the integers in the range of $[0, 255]$ to produce the output image J.

The relationship between DCT coefficient d_1 and its quantized and dequantized version d_1' can be formulated as follows:

$$d_1'(i,j) = \left[\frac{d_1(i,j)}{q}\right] \times q, \quad 0 \leq i,j \leq 7 \tag{1}$$

where $q = Q(i,j)$ denotes the quantization step.

The previous research in [13] and [14] has shown that the ac coefficients $d_1(i,j)$ $((i,j) \neq (0,0))$ of natural images can be approximately modeled as a Laplacian distribution with a mean around zero, as shown in Fig. 2(a). After quantization and dequantization, most values in the histogram of d_1 will be quantized to their nearest integers of kq, where k is an integer. As illustrated in Fig. 2(b), it is observed that the continuous values of d_1 will be reduced to a small quantity of integers that are multiples of the quantization step q.

Note that we cannot recover the d_1' exactly from a decompressed image J due to the deterministic rounding (and truncating) in the JPEG decoder. As illustrated in Fig. 3, we just obtain an approximative version of d_1' (denoted as d_2) via performing the forward DCT on each nonoverlapping 8×8 of the output image J. It is also shown that the difference between d_1' and d_2 can be regarded as an approximate Gaussian distribution with mean 0 and variance 1/12. In such a case, the coefficients d_2 will not appear at the multiples of the quantization step q exactly, but spread around them at a limited range of $(-1, +1)$, just as illustrated in Fig. 3.

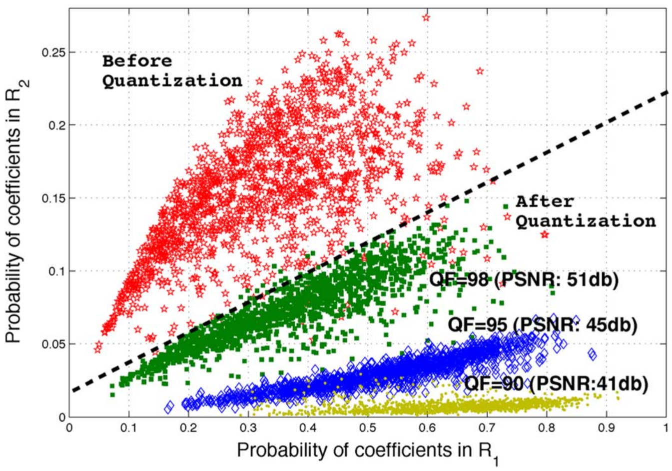


Fig. 4. Distributions of the 2-D features for original images and their JPEG compressed versions with quality factors of 98, 95, and 90.

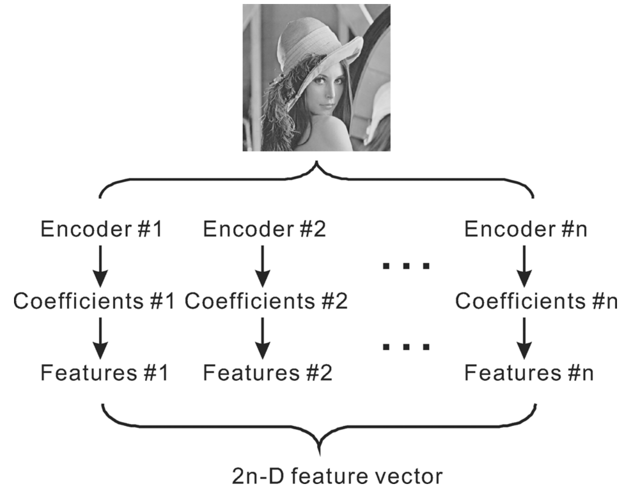


Fig. 5. Feature extraction.

The quantization artifacts detection is then converted to distinguish the histograms between Fig. 2(a) (before quantization) and Fig. 3 (after quantization). It is observed that the number of the corresponding ac components d_2 in the region $R_1 = (-1, +1)$ will increase, while the number in the region $R_2 = (-2, -1] \cup [+1, +2)$ will decrease significantly, when the quantization step is larger than 2, which means that

$$\int_{R_1} p_2(y)\,dy = \int_{-1}^{+1} p_2(y)\,dy \approx p'_1(0) = \int_{-\frac{q}{2}}^{+\frac{q}{2}} p_1(y)\,dy \geq \int_{-1}^{+1} p_1(y)\,dy = \int_{R_1} p_1(y)\,dy, \quad q \geq 2 \tag{2}$$

and

$$\int_{R_2} p_2(y)\,dy = \int_{-2}^{-1} p_2(y)\,dy + \int_{+1}^{+2} p_2(y)\,dy \approx 0 + 0 \leq \int_{R_2} p_1(y)\,dy, q \geq 2 \tag{3}$$

where p_1, p'_1, and p_2 denote the probability density function (pdf) of the coefficients d_1, d'_1, and d_2 (except for the dc component), respectively.

Formulas (2) and (3) show that we can just investigate the probability of the ac components in the regions R_1 and R_2 to identify whether a given bitmap image is an original uncompressed image (d_1) or a JPEG quantized one (d_2).

Fig. 4 shows the distributions of 2-D features (namely, the probabilities of the ac components in R_1 and R_2) for uncompressed images and their JPEG compression versions with quality factors of 98, 95, and 90. In the experiments, the 1338 test images come from UCID [15]. It is clearly observed that the features between the uncompressed and JPEG images are mostly separate, even for the images after slight compression, e.g., the quality factor as high as 98 (the average PSNR is 51 dB in such a case).

The above experimental results show that the proposed 2-D features are very sensitive to quantization operation. Note that the quantization artifacts can be analyzed similarly for other transform codings (as well as various sub-band codings, differential image encoders, etc.) as long as we can follow the same compression procedure and get the coefficients (or their approximate versions) before the quantization operation. In the following Section III, we will use the proposed features to identify the source encoder from a given bitmap image.

III. Identification of Transform Encoder

Given a bitmap image without any previous compression information, our proposed method is to identify its original source encoder from some candidates (and/or the same type of source encoder with different parameters). As mentioned previously, the quantization operation is usually a necessary step in most lossy compression schemes. Since different encoders employ different transforms (such as DCT, DWT, Hadamard, etc.) and/or different parameters (such as the block sizes and decomposition levers, etc.), it is expected that the quantization artifacts will become obvious only at the corresponding coefficients that have been quantized previously, which indicates the original source encoder as well as its encoder parameters of the image. For instance, the quantization artifacts found in DCT ac components reveal the image was compressed using a JPEG scheme (see Section II), while the artifacts occurring at the wavelet coefficients shows that the image may have been originally compressed using a JPEG2000 scheme, and so on. By checking the quantization artifacts for all possible coefficients using our proposed 2-D features, it is possible to determine the original encoder of the given image. Therefore, the proposed method is given as follows.

Assume that the questionable image is I, and the total number of the possible source encoders (the combination of transforms and parameters) is n. As illustrated in Fig. 5, for each candidate encoder, we first follow the compression procedure and stop before the quantization operation. We then extract the 2-D features from the histograms of the corresponding transform coefficients as illustrated in Section II, and finally combine these features as a feature vector ($2n$ dimensions). The feature vector is then fed to a support vector machine (SVM) to train a classifier.

IV. Experimental Results

In the experiments, we randomly chose 1000 images from the UCID [15] and NRCS datasets [16], respectively. Besides

TABLE I
CONFUSION MATRIX FOR TRANSFORMS IDENTIFICATION. THE ASTERISK (*) DENOTES THE VALUES LESS THAN 1%. (AVERAGE ACCURACY: 99.4%)

		Original	8×8			whole image			
			DCT	Hadamard	Slant	bior4.4	Harr	db5	sym7
Original		**99.8%**	0	0	*	*	*	*	*
8×8	DCT	0	**100%**	0	0	0	0	0	0
	Hadamard	*	0	**99.9%**	0	0	0	0	0
	Slant	0	0	0	**100%**	0	0	0	0
whole image	bior4.4	*	0	0	0	**98.0%**	*	*	*
	Harr	*	0	*	0	0	**99.2%**	*	*
	db5	*	0	0	0	*	*	**98.9%**	*
	sym7	*	0	*	0	*	*	*	**99.1%**

that, we took 3000 images which were originally stored in raw or TIFF format using six different digital cameras (Nikon D40, D50, and D300, Panasonic DMC-FZ30, Minolta A2 and D5D). In all, there are 5000 uncompressed natural images with various scenes and lighting conditions. All the color images are first converted to gray-scale images and reduced to different sizes ranging from 384×512 to 768×512. In the following, only 1/5 of the images are randomly selected in the training stage, and the remaining 4000 images are used for the testing. The LibSVM tool [17] (using the "easy.py" command in the tool written with Python, Version # 2.9) has been employed to train an SVM classifier.

A. Identifying JPEG Images

In this experiment, we try to determine whether a given image has been JPEG compressed previously or not. Four commonly used editing softwares have been used for JPEG compression, including Matlab, GIMP, ACDSee with a random quality factor ranging from 85 to 95[1] (see Fig. 4), and Photoshop with higher quality levels from 6 to 11 (the highest quality level is 12). The average PSNR of the JPEG images is 42.31 dB.

For each image, we first divide it into 8×8 nonoverlapping blocks, and then extract the 2-D quantization features from all the DCT ac components, as described in Section II. The testing results show that our proposed method can distinguish the JPEG images from the uncompressed ones very reliably with an average accuracy of 98.71%.

Note that the proposed method cannot identify JPEG images with different softwares since they employ the same transform and block size: this would be the subject of our further work.

B. Identifying the Transforms

In this experiment, we try to identify the type of transforms during compression. Seven transforms have been evaluated. The three block-based transforms, including DCT, Hadamard, and Slant, use a block size of 8×8 and use the baseline JPEG compression with a standard quantization table as it did in [8]. Here, the quality factors are also randomly selected in the range of $\{85, 86, \ldots, 95\}$. Other four wavelet-based transforms, including bior4.4, Harr, db5, and sym7, use five-level decomposition over the whole image. For each sub-band, we assigned a random quantization step ranging from $(1, 10]$ (note that for error-free compression, the quantization step is equal to 1). The average PSNRs of the test images we obtained are 41.2, 39.3, 40.2, 37.3, 37.8, 37.2, and 37.1 dB, respectively.

As shown in Fig. 5, we can get a 14-D feature vector for each test image. For the three block-based transforms, the 2-D features are extracted from the corresponding frequency coefficients, while for the four wavelet-based transforms, the 2-D features are extracted from the HH_1 sub-band coefficients using the corresponding wavelet basis, respectively. The feature vectors of the training images are first used to train an SVM classifier, which is then applied to identify the source transforms from a given test image. The confusion matrix evaluated on the testing data is shown in Table I.

We can see that the proposed method can reliably differentiate between the images using Slant transform and DCT, which overcomes the limitations in the previous method [8]. What is more, our average accuracy can achieve as high as 99.4% even when the PSNR is larger than 37 dB.

C. Identifying the Block Sizes

In this experiment, we try to identify the block sizes during image partition (for the first step in the transform coding system, see Fig. 1). Similar to the existing works [7], [10], [11], for each image in our image database, we first divide it into nonoverlapping blocks with five different block sizes ranging from 4×4 to 64×64; we then simulate baseline JPEG compression on each block with a corresponding quantization table scaled from the 8×8 standard one. Here, the quality factors of the standard tables are randomly selected in the range of $\{85, 86, \ldots, 95\}$, and the average PSNRs of the test images we obtained are 41.0, 41.1, 41.0, 40.8, and 40.5 dB, respectively.

For each test image, we extract the 2-D features from the DCT ac components with the corresponding five blocking sizes, independently. In all, there are 10-D features for each image. Similarly, the SVM technology is used in the training and testing stages, and the confusion matrix for the testing data is shown in Table II.

It is observed that the average accuracy can achieve over 99.9%, even when the PSNR of the test image is higher than 40 dB for all the block sizes, which is a significant improvement on the existing works [7], [10], [11] based on the blocking artifacts detection. For instance, the average accuracy is around 90% for our previous method [11] and around 75% for the methods in [7] and [10] when the block size is 8×8, and the accuracy usually drops with increasing block sizes for the existing approaches. See [11] for more details.

[1]The smaller the quality factors we use, the larger the distances between the uncompressed and JPEG compressed image we obtain in the feature space, and thus it is easier to identify those JPEG images with smaller quality factors. In the experiments, we just investigate the higher quality images after slight quantization, e.g., QFs in 85–95 in this paper.

TABLE II
CONFUSION MATRIX FOR BLOCK SIZE ESTIMATION. (AVERAGE ACCURACY: 99.9%)

	Original	4×4	8×8	16×16	32×32	64×64
Original	**99.9%**	0	0	0	*	*
4×4	*	**99.9%**	0	0	0	0
8×8	0	0	**100%**	0	0	0
16×16	0	0	0	**100%**	0	0
32×32	*	0	0	0	**99.9%**	0
64×64	*	0	0	0	*	**99.9%**

TABLE III
CONFUSION MATRIX FOR DECOMPOSITION LEVELS IDENTIFICATION USING THE SCALAR QUANTIZATION. (AVERAGE ACCURACY: 86.0%)

	Original	1-level	2-level	3-level	4-level	5-level
Original	**99.2%**	*	*	*	*	*
1-level	3.1%	**95.6%**	*	*	*	*
2-level	*	8.2%	**88.9%**	1.5%	*	*
3-level	*	1.5%	10.0%	**83.6%**	2.9%	1.9%
4-level	*	1.4%	2.5%	12.2%	**74.2%**	9.4%
5-level	*	*	1.6%	5.6%	17.3%	**74.5%**

TABLE IV
CONFUSION MATRIX FOR DECOMPOSITION LEVELS IDENTIFICATION WITH THE SPIHT APPROACH. (AVERAGE ACCURACY: 98.5%)

	Original	1-level	2-level	3-level	4-level	5-level
Original	**99.7%**	*	*	*	0	*
1-level	0	**100%**	0	0	0	0
2-level	0	*	**99.8%**	*	*	*
3-level	*	*	*	**98.9%**	*	*
4-level	*	*	*	*	**96.4%**	3.1%
5-level	*	*	*	*	2.4%	**96.6%**

D. Identifying the Decomposition Levels

In this experiment, we try to identify the levels during the wavelet decomposition. We first decompose original images with wavelet bior4.4 basis, and then obtain five test images using different levels ranging from 1-level to 5-level. Two quantization methods have been employed. The first is the conventional scalar quantization as used in Subsection IV-B (the PSNRs of the resulting images are around 37 dB in such cases). The other is the set partitioning in hierarchical trees (SPIHT) approach with a bit rate of 1 bpp. We obtain the test images with average PSNRs of 24.8, 35.7, 37.4, 37.7, and 37.8 dB, respectively.

In order to obtain the feature vector of the test image, we repeat the decomposition process 5 times using the same basis, and then extract the 2-D features as described in Section II for each HH_i sub-bands, where $i = 1, 2, 3, 4, 5$. Therefore, there are 10-D features for each image. It is expected that if a given image has been i-levels decomposed and quantized, then the corresponding sub-bands $HH_1, HH_2, \ldots, HH_i$ will present the quantization artifacts as shown in Fig. 3, while for the sub-bands $HH_{i+1}, HH_{i+2}, \ldots$ without being quantized, those quantization artifacts will not become obvious. These patterns can be easily reflected in the proposed 10-D features. The confusion matrices evaluated on the testing data using the two quantization approaches are shown in Tables III and IV, respectively.

From Table III, it is observed that the average accuracy usually decreases with increasing decomposition levels. For instance, the accuracy is around 95.6% for identifying the images with 1-level multiresolution decomposition, while it drops to 74.5% when the level becomes 5. One of the reasons is that the sizes of the $HH_i, i = 1, 2, \ldots$ will exponentially decrease. Taking an image of 512×512 for example, the size of the sub-band HH_5 will reduce to 16×16 after 5-levels decomposition. Therefore, the average accuracy will decrease due to an insufficient number of effective data samples for extracting the feature vector.

Unlike the scalar quantization in our simulation experiment, which assigns the quantization steps without considering the relationships between the sub-bands of an image, the SPIHT approach can fully exploit the inherent similarities among the sub-bands in a wavelet decomposition of an image (e.g., the sub-bands of $HH_i, i = 1, 2, 3, 4, 5$) and assigns the quantization steps adaptively. In such cases, more detectable artifacts will be introduced into the resulting images. First of all, the quantization artifacts will be presented at each separate sub-band. Second, there must exist some inherent relationships between the sub-bands of $HH_i, i = 1, 2, \ldots, n$ of an image after n-level decomposition. It is expected that the proposed 10-D feature vector contains much information that contributes to the classification, and thus it is easier to identify the images using the SPIHT approach than by those using the random quantization. As shown in Table IV, we can achieve an average accuracy as high as 98.5%, which is much better than the performances shown in Table III with an average accuracy of 86.0%.

V. Concluding Remarks

Quantization is one of the necessary steps in most lossy image compression schemes, and it will introduce some inherent artifacts into the corresponding coefficients of resulting images. Similar to other forensics algorithms, e.g., [4] and [6], an effective way for detecting or measuring the quantization artifacts is one of the main contributions of this paper. Moreover, we convert the forensic problem of source encoder identification into quantization artifacts detection, and propose an effective feature vector to identify the source encoder as well as some parameters from a decompressed image, by detecting the quantization artifacts on the possible transform coefficients using all candidate source encoders. The extensive experimental results show the effectiveness of the proposed method.

For some source encoders, such as some prediction coding employed in image/video compression, we cannot follow the same compression procedure and obtain the corresponding coefficients before the quantization operation from a decompressed image due to the lack of prediction parameters. In such cases, we need to combine with other approaches such as [7] to first estimate the residues (i.e., the coefficients before quantization), and then apply our method to extract the 2-D features from the histogram of the residues.

As the first step for image source encoders identification, as in all the existing works [7]–[11], we assume that the given bitmap images have not been altered by any postimage processing in this paper. How to resist the commonly used processing, such as adding noise and recompression, will be carefully considered in our further works.

We hope that the proposed scheme can be combined with previous methods and/or future works to make image source encoder identification more reliable.

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