Detecting Double JPEG Compression With the Same Quantization Matrix

Fangjun Huang, *Member, IEEE*, Jiwu Huang, *Senior Member, IEEE*, and Yun Qing Shi, *Fellow, IEEE*

***Abstract*—Detection of double joint photographic experts group (JPEG) compression is of great significance in the field of digital forensics. Some successful approaches have been presented for detecting double JPEG compression when the primary compression and the secondary compression have different quantization matrixes. However, when the primary compression and the secondary compression have the same quantization matrix, no detection method has been reported yet. In this paper, we present a method which can detect double JPEG compression with the same quantization matrix. Our algorithm is based on the observation that in the process of recompressing a JPEG image with the same quantization matrix over and over again, the number of different JPEG coefficients, i.e., the quantized discrete cosine transform coefficients between the sequential two versions will monotonically decrease in general. For example, the number of different JPEG coefficients between the singly and doubly compressed images is generally larger than the number of different JPEG coefficients between the corresponding doubly and triply compressed images. Via a novel random perturbation strategy implemented on the JPEG coefficients of the recompressed test image, we can find a "proper" randomly perturbed ratio. For different images, this universal "proper" ratio will generate a dynamically changed threshold, which can be utilized to discriminate the singly compressed image and doubly compressed image. Furthermore, our method has the potential to detect triple JPEG compression, four times JPEG compression, etc.**

***Index Terms*—Digital forensic, double joint photographic experts group (JPEG) compression, quantization matrix.**

I. Introduction

DOUBLE joint photographic experts group (JPEG) compression means that a JPEG image has been compressed once again by JPEG compression. The detection of double JPEG compression is of great significance in digital forensics. There are at least two reasons why forensic experts pay attention to the detection of double JPEG compression [1], [2]. The first one is that the doubly compressed JPEG images often result from image forgery. For example, in image-splicing, one part of the source image is copied to the target image to generate a new composite image. If the source image or target image is in JPEG format, the spliced image may need to be JPEG compressed, hence exhibiting traces of double JPEG compression. These traces can be used to detect the forgery image or even identify the manipulated areas [3], [4]. The second one is that some JPEG steganographic schemes such as F5 [5] and OutGuess [6] may generate doubly compressed images if the input cover image is in JPEG format. Detection of double JPEG compression can help to identify the steganographic algorithm or improve the detection accuracy rate of the steganalytic schemes. Furthermore, in addition to the aforementioned two applications, the techniques and methods resulted from the research of double JPEG compression detection can also be applied to digital audio [7] and digital video [8], [9] forensics.

Recently, some successful approaches have been presented for detecting double JPEG compression when the primary compression and the secondary compression have different quantization matrixes (sometimes referred to as quantization tables). Lukáš and Fridrich [1] addressed the distribution of JPEG coefficient (i.e., the quantized discrete cosine transform (DCT) coefficient) histogram of the individual mode in a doubly compressed JPEG image, and pointed out that some abnormal properties such as "missing values" and "double peak" might exist in the JPEG coefficient histogram if the primary compression and the secondary compression had different quantization matrixes. Three different approaches that could estimate the primary quantization matrix from the doubly compressed image were presented. Popescu and Farid [10], [11] also pointed out that different quantization matrixes in the primary and the secondary compression might introduce some abnormal patterns in the JPEG coefficient histogram of the individual mode, and a doubly compressed JPEG image could be detected via evaluating the periodic property belonging to the Fourier transform of the JPEG coefficient histogram of the individual mode. In [12], Fu *et al.* presented a model called generalized Benford's law to fit the distribution of the first digits of JPEG coefficients from all JPEG alternate current (ac) modes. Through observing whether the distribution fits the presented model, double JPEG compression can be detected. In [13], Li *et al.* pointed out that through using generalized Benford's law to fit distribution of the first digits of JPEG coefficients from some selected individual ac modes, the performance of detecting double JPEG compression could be greatly enhanced. Combined with a

Manuscript received April 08, 2010; revised August 25, 2010; accepted August 26, 2010. Date of publication September 02, 2010; date of current version November 17, 2010. This work was supported by the 973 Program of China (Grant 2011CB302204), by the National Natural Science Foundation of China (Grant 60633030), and by the Research Fund for the Doctoral Program of Higher Education of China (Grant 20070558054). The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Wenjun Zeng.

F. Huang was with the Department of Electrical and Computer Engineering, New Jersey Institute of Technology, NJ 07102 USA. He is with the School of Information Science and Technology, Sun Yat-Sen University, Guangzhou, GD 510006, China (e-mail: huangfj@mail.sysu.edu.cn).

J. Huang is with the School of Information Science and Technology, Sun Yat-Sen University, Guangzhou, GD 510006, China, and is also with the State Key Laboratory of Information Security, Institute of Software, Chinese Academy of Sciences, Beijing, 100190, China (e-mail: isshjw@mail.sysu.edu.cn).

Y. Q. Shi is with the Department of Electrical and Computer Engineering, New Jersey Institute of Technology, NJ 07102 USA (e-mail: shi@njit.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TIFS.2010.2072921

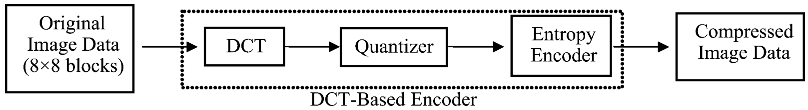


Fig. 1. Block diagram of JPEG compression process.

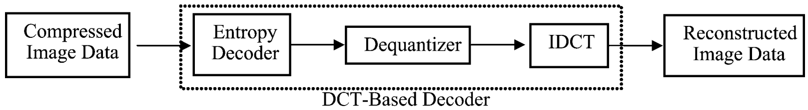


Fig. 2. Block diagram of JPEG decompression process.

multiclass classification strategy, the quality factor (QF) in the primary JPEG compression can be identified. In [14], Chen *et al.* presented another machine-learning-based scheme, in which 324 features were extracted from each given JPEG image. With the help of a support vector machine (SVM), the doubly and singly compressed JPEG images can be distinguished effectively.

However, all the existing algorithms can only detect double JPEG compression when the primary compression and the secondary compression use different quantization matrixes. If the primary compression and the secondary compression have the same quantization matrix, the abnormality introduced by different quantization matrixes does not exist so that the previous detection methods targeted for double JPEG compression with different quantization matrixes cannot work. To the best of our knowledge, there is no detection method reported in the literature that can detect double JPEG compression with the same quantization matrix used in the two JPEG compressions.

In this paper, we present a method to detect double JPEG compression with the same quantization matrix. Due to the three kinds of errors (i.e., quantization error, truncation error, and rounding error) in JPEG compression and the decompression procedure, even if the singly compressed image is recompressed again with the same quantization matrix, some JPEG coefficients will still be modified, and the obtained doubly compressed image may have some difference to the original singly compressed image. Furthermore, when recompressing the JPEG image over and over again, the number of different JPEG coefficients between the sequential two versions will monotonically decrease in general. For example, the number of different JPEG coefficients between the singly and doubly compressed images is generally larger than the number of different JPEG coefficients between the corresponding doubly and triply compressed images. Our detection method is based on a novel random perturbation strategy implemented on the JPEG coefficients of the recompressed test image. Via using this new random perturbation strategy, a "proper" randomly perturbed ratio can be found. For different images, this universal "proper" ratio will generate a dynamically changed threshold, which can be utilized to discriminate the singly compressed image and doubly compressed image. Furthermore, our method has the potential to detect triple JPEG compressed, four times JPEG compression, etc.

The rest of this paper is organized as follows. In Section II, our new detection algorithm is presented. The experimental results and discussions are provided in Section III, and the conclusion is drawn in Section IV.

II. Proposed Detection Scheme

In this section, the three different kinds of errors that may introduce the disturbance to doubly compressed image are analyzed first, based on a brief review of the JPEG compression and decompression process. Then, through extensive experiments, we demonstrate that some statistical difference does exist between the singly compressed and doubly compressed images. Moreover, the statistical difference between the sequential two versions will monotonically decrease as we recompress the image over and over again with the same quantization matrix. At last, we present a new random perturbation strategy which can be used to detect the double JPEG compression.

A. Three Kinds of Errors Existing in JPEG Compression and Decompression Process

The key steps of JPEG compression and decompression process [15] are shown in Figs. 1 and 2, respectively. These figures illustrate the special case of grayscale image compression and decompression. A color image can be approximately regarded as multiple grayscale images. Without loss of generality, we suppose that the pixel values of the image in the spatial domain are represented by the integral numbers in the range $[0,\ 255]$.

As we know, the DCT-based JPEG compression is a lossy compression method. There are three different kinds of errors in the compression and decompression procedure. The first one is the quantization error, which exists in the compression process. By applying the two-dimensional DCT to the nonoverlapping 8×8 blocks of the original image data, we will obtain the DCT coefficients. The obtained coefficients are then fed to the quantizer. In the quantizer, the DCT coefficients are divided by the quantization steps and then rounded. The difference between the actual float value of the divided DCT coefficients and the rounded integer value (i.e., the aforementioned JPEG coefficients) is called quantization error. The second and third kinds of errors both exist in the decompression process. After applying inverse DCT (IDCT) to the dequantized JPEG coefficients, the obtained float numbers need to belong to the region $[0,\ 255]$ in spatial domain. In order to reconstruct the image data, the values that do not belong to $[0,\ 255]$ would be truncated to 0 or 255, respectively. That is, if the pixel value in the reconstructed image is less than 0, it is truncated to 0; if the reconstructed pixel value is larger than 255, it is truncated to 255. This kind of error is called truncation error. In addition, the float numbers belonging to $[0,\ 255]$ are needed to be rounded to the nearest integer value while reconstructing the image in

TABLE I
RANGES OF C_1 AND THE AVERAGE VALUES OF C_1 BETWEEN THE SINGLY AND DOUBLY COMPRESSED JPEG IMAGES FROM DIFFERENT IMAGE DATASETS

Quality Factor (QF)	Range of C_1			Average values of C_1		
	UCID	NRCS	OurLab	UCID	NRCS	OurLab
70	0~0.05368	0~0.05063	0~0.03674	0.00307	0.00095	0.00087
75	0~0.04929	0~0.04999	0~0.03716	0.00303	0.00096	0.00088
80	0~0.05121	0~0.04899	0~0.03844	0.00386	0.00116	0.00102
85	0~0.04894	0~0.04816	0~0.03539	0.00377	0.00113	0.00093
90	0.00002~0.04783	0.00004~0.05248	0.00003~0.03551	0.00428	0.00133	0.00104
95	0.01375~0.09277	0.01544~0.07051	0.01383~0.05139	0.02988	0.02533	0.02479
100	0.05495~0.11672	0.05512~0.10071	0.05431~0.08573	0.06823	0.06312	0.06228

the spatial domain. The error existed in the rounding process is called the rounding error.

Because of the aforementioned three kinds of errors, i.e., quantization error, truncation error, and rounding error, the doubly compressed image may have some difference from the original singly compressed image even if the image is doubly compressed with the same quantization matrix as that of the singly compressed image.

B. *Statistical Difference Between Singly Compressed JPEG Image and Doubly Compressed JPEG Image*

Suppose the JPEG image is denoted by $J_n(n = 1, 2, \ldots)$, where n represents the number of times that this image has been JPEG compressed. For example, J_1 means that this image is a singly compressed JPEG image, and J_2 means that the image has been doubly JPEG compressed. The number of nonzero JPEG coefficients in J_n is represented as S_n, and the number of different JPEG coefficients between J_n and J_{n+1} is represented as $D_n(n = 1, 2, \ldots)$. The rate of coefficient change between J_n and J_{n+1} is defined as C_n, and $C_n = D_n/S_n(n = 1, 2, \ldots)$.

Three different image datasets are used to exemplify the statistical difference between the singly compressed JPEG image and doubly compressed JPEG image. All the images are uncompressed color images originally. Among them, 1338 images with the size 384×512 or 512×384 were downloaded from the Uncompressed Colour Image Database (UCID) [16], 1543 images were downloaded from the Natural Resources Conservation Service (NRCS) [17] which were central cropped with the size 512×768, and an additional 1128 images with the size 512×512 were taken by group members of Our Laboratory (OurLab) in different places with different cameras. All these images are converted to grayscale images first, and then the obtained grayscale images are JPEG compressed for studying the difference between the singly compressed image and doubly compressed image. It is noted that for doubly compressed JPEG images in this paper, the secondary compression has the same quantization matrix as that in the primary compression.

The quantization matrixes corresponding to the standard JPEG compression with QF $= 70,\ 75,\ 80,\ 85,\ 90,\ 95,\ 100$ are selected for testing. The aforementioned three image datasets are tested separately. In Table I, the ranges of C_1 and the average values of C_1 regarding different QFs are listed. It is observed from Table I that for images belonging to different datasets, the ranges of C_1 may be different, which means that the images in different datasets may have different behaviors when recompressing them using the same quantization matrix. Furthermore, it is observed from Table I that for any image dataset, the values of C_1 are distributed in a rather wide range, which means that the images in the same datasets may also have different behaviors in the recompression process. In addition, from the average values of C_1, we can find out that in general, the difference between the singly compressed image and doubly compressed image is small when the primary compression and the secondary compression have the same quantization matrix. For example, for these three image datasets, the average values of C_1 are less than 7% for any image QF, especially when the QF is no more than 90, the rate of change C_1 is less than 0.5%. It is difficult to detect such small difference as indicated in [14].

C. *Statistical Analysis of Multiple JPEG Compression With the Same Quantization Matrix*

Before presenting our detection method, we study the variation tendency of $D_n(n = 1, 2, \ldots)$ between the sequentially JPEG compressed images. The experiments are also conducted on the three image datasets separately. The variation tendency of $D_n(n = 1, 2, \ldots, 10)$ corresponding to different QFs are illustrated in Fig. 3, where the horizontal axis represents the index n of $D_n(n = 1, 2, \ldots, 10)$, and the vertical axis represents the average values of D_n for all the images in the same image dataset. Because the average values of D_n corresponding to QF $= 95,\ 100$ are much bigger than those corresponding to the QFs from 70 to 90, we illustrate them separately. It is observed from Fig. 3 that, no matter what image dataset or image QF is selected, for $n = 1, 2, 3, \ldots$, the average values of D_n are larger than the average values of D_{n+1}, and the intervals between the average values of D_{n+1} and D_n are wider than those between D_{n+2} and D_{n+1} in general. These experimental results demonstrate that when recompressing the JPEG image over and over again with the same quantization matrix, the number of different JPEG coefficients between the sequential two versions will monotonically decrease. This intrinsic property of the JPEG image can be utilized by us to discriminate the singly compressed image and doubly compressed image.

D. *Detection of Double JPEG Compression With Random Perturbation Strategy*

Given a JPEG image J under examination, our detection method is proposed as follows. Please note that decompressing the JPEG image includes four steps (as shown in Fig. 2), i.e., entropy decoding, dequantizing, IDCT, and reconstructing. In

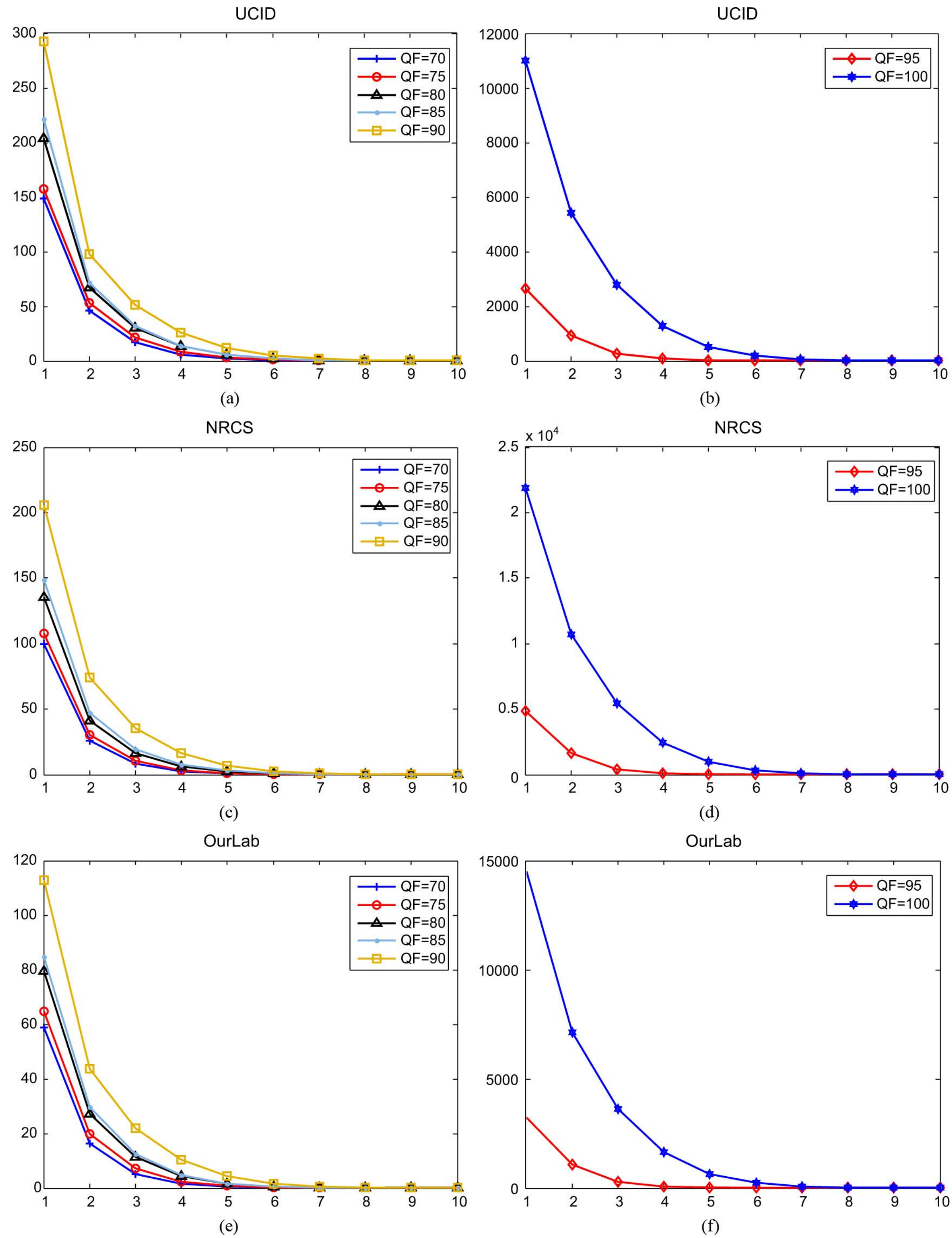


Fig. 3. Variation tendency about the average values of $D_n (n = 1, 2, \ldots, 10)$ for three different image datasets with different image QFs, where the horizontal axis represents the index n of D_n, and the vertical axis represents the averages values of D_n for all the images in the same image dataset. (a) UCID image dataset with QFs from 70 to 90 with an increment of 5; (b) UCID image dataset with QFs 95 and 100; (c) NRCS image dataset with QFs from 70 to 90 with an increment of 5; (d) NRCS image dataset with QFs 95 and 100; (e) OurLab image dataset with QFs from 70 to 90 with an increment of 5; (f) OurLab image dataset with QFs 95 and 100.

our presentation next, decompressing a JPEG image into the spatial domain means that we will complete all four decompressing steps.

1) Decompress J into the spatial domain, and then recompress it using the same quantization matrix. We obtain the JPEG image J'. The number of different JPEG coefficients between J and J' is denoted by D.
2) Entropy decode J' to have its JPEG coefficients, and randomly select a portion of the obtained JPEG coefficients (including all coefficients in direct current (dc) components and ac components) for modification. Each of the randomly selected coefficients is decreased or increased by 1 arbitrarily. Then entropy encode the modified JPEG coefficients again to have the JPEG image J'_m. The ratio of

coefficients that should be modified is denoted by $mpnc$ (the number of modified coefficients per nonzero JPEG coefficients). It is noted that in this step, we do not decompress the JPEG image J' into the spatial domain, and only conduct entropy decoding to have its JPEG coefficients for modification. After modification, the modified JPEG coefficients are entropy encoded to get the JPEG image J'_m directly (the entropy decoding and encoding process can be conducted with the help of the JPEG Tool Box [18]).

3) Decompress J'_m into the spatial domain and then recompress it with the same quantization matrix. We can obtain the JPEG image J''_m. The number of different JPEG coefficients between J'_m and J''_m is represented by D_m.
4) Repeat steps 2 and 3 for k times. Note that in each time, the JPEG coefficients of J' to be modified are randomly selected, but the ratio of JPEG coefficients that should be modified remains the same. Each time we may have a different value D_m, represented by $D_m^1, D_m^2, \ldots, D_m^k$, respectively. The average value is $\bar{D}_m = (D_m^1 + D_m^2 + \cdots + D_m^k)/k$. Our decision rule is

$$\begin{cases} \text{if } \bar{D}_m \geq D, & J \text{ is a doubly compressed image} \\ \text{if } \bar{D}_m < D, & J \text{ is a singly compressed image.} \end{cases} \tag{1}$$

It is noted that in step 1, we do not know whether the test JPEG image J is singly or doubly compressed. However, if the test image is a singly compressed image, a relatively big value D will be obtained since in this condition $D = D_1$. Otherwise, if the test image has been doubly compressed, we will get a relatively small value D since in this condition $D = D_2$. That is, the value of D is determined by the test image; i.e., if the test image is singly compressed, the value of D will be relatively big, and if the test image is doubly compressed, the value of D will be relatively small. Then after conducting the following two steps (i.e., steps 2 and 3 of our detection algorithm), the obtained value of $\bar{D}_m$, which is mainly determined by the modified ratio, will have more chances to be less than D when the test image is singly compressed than that when the test image is doubly compressed. For the same reason, the obtained value of $\bar{D}_m$ will have more chances to be no less than D when the test image is doubly compressed than that when the test image is singly compressed. This is the logic underlining the decision rule of (1).

As seen, the key for the success of our detection method is the portion of JPEG coefficients that should be modified. The modified portion being selected too big or too small will not lead to a good detection result. For example, if the modified ratio is selected as 1, the obtained value of $\bar{D}_m$ may be bigger than D in general no matter whether the test image is singly or doubly compressed. Thus even if the test image is a singly compressed image, it will be determined as a doubly compressed image according to (1). As to our method, the main challenge is to find the "proper" ratio, which can make the obtained $\bar{D}_m$ be less than D if the test image is a singly compressed image (note that in this condition the obtained $D = D_1$), and no less than D if the test image is doubly compressed (note that in this condition the obtained $D = D_2$). Namely, if we can find a "proper" ratio, which can make the value of $\bar{D}_m$ belong to the region of $[D_2,\ D_1)$, a correct decision can be made according to (1). However, since images are complicated, in order to make $\bar{D}_m$ belong to the region of $[D_2,\ D_1)$, we may need to apply different "proper" ratios to different images. If so, it will greatly limit the application of our proposed method. In Section III, we will demonstrate that for different images with the same QF, a universal "proper" ratio does exist. In addition, if we can find the "proper" ratio that will make $\bar{D}_m$ belong to the region of $[D_3,\ D_2)$ or $[D_4,\ D_3)$, this proposed method also works in determination of the triple JPEG compression or four times JPEG compression, etc.

III. Experimental Results and Discussions

All our experiments are conducted on the aforementioned three image datasets, i.e., UCID, NRCS, and OurLab. For each image in these three datasets, a singly compressed image and doubly compressed image are generated, respectively. Detection of double JPEG compression is a two-class prediction problem (binary classification), in which the outcomes are labeled either as positive or negative class. In our experiments, true positive means that the doubly compressed image is predicted as doubly compressed image, and true negative means that the singly compressed image is predicted as singly compressed image. Consequently, false negative means that the doubly compressed image is predicted as a singly compressed image, and false positive means that the singly compressed image is predicted as a doubly compressed image. Since the singly compressed images and doubly compressed images to be detected have the same quantities in our experiments, the final detection accuracy rate (AR) is computed as $\text{AR} = (\text{TPR} + \text{TNR})/2$, where TPR and TNR represent the true positive rate and true negative rate, respectively.

A. "Proper" Ratio for Different Image Datasets

As mentioned in Section II-D, the key issue of our method is in the second step, i.e., the "proper" ratio of JPEG coefficients that should be chosen for modification. After finding the "proper" ratio, the corresponding $\bar{D}_m$ can be obtained. Through comparing $\bar{D}_m$ with D (where D represents the number of different JPEG coefficients between the test JPEG image and recompressed JPEG image), the test image can be predicted as a singly compressed or a doubly compressed image according to (1). In our experiments, we determine the "proper" ratios through exhaustive search. According to the experimental results in Section II, the difference between the singly compressed image and its corresponding doubly compressed image is rather small in general. Thus the modified ratio cannot be selected too big. Otherwise, the corresponding value of $\bar{D}_m$ will be bigger than D no matter whether the test image is doubly compressed or not. According to the decision rule in (1), if $\bar{D}_m > D$, the test image will be predicted as doubly compressed image even if it is a singly compressed image. Consequently, in our experiments, the modified ratio, represented by $mpnc$, is changed from 0 continuously with a step of 0.001. Our experiments demonstrate that when the modified ratio is increased to 0.118, most of the singly compressed images are predicted as doubly compressed image and the final detection accuracy rate will not increase. So we stop our experiments at this point. In our experiments, two types of images, i.e., singly compressed image and doubly

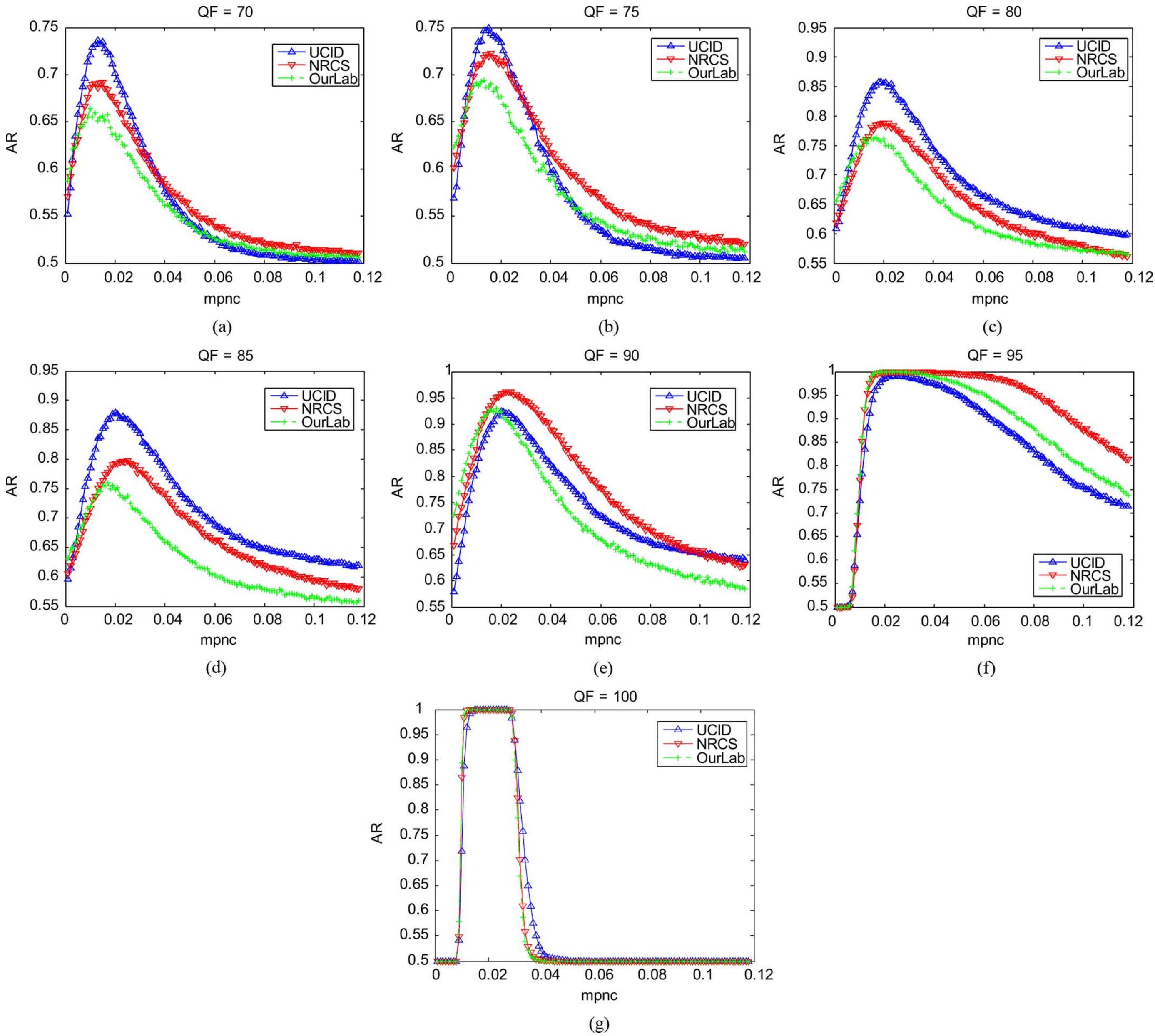


Fig. 4. Detection accuracy rates corresponding to different image datasets and different QFs, where the horizontal axis represents the $mpnc$ value and the vertical axis represents the detection accuracy rate (a) QF $= 70$; (b) QF $= 75$; (c) QF $= 80$; (d) QF $= 85$; (e) QF $= 90$; (f) QF $= 95$; (g) QF $= 100$.

compressed image are generated first, and each image dataset is tested separately to find the "proper" ratio. For any modified ratio between 0 and 0.118, our experiment is conducted as follows.

1) According to the four steps in Section II-D, each singly compressed image in the image dataset is tested first. For each image, two values of D and $\bar{D}_m$ will be obtained. Note that in this condition, the value of D is equal to D_1 since the images are singly compressed. According to the decision rule in (1), if $\bar{D}_m < D$, the test image will be correctly predicted as a singly compressed image. Otherwise, a wrong decision will be made. The probability that the singly compressed has been correctly predicted is represented by TNR.
2) Then the same modified ratio is also used to test the doubly compressed images in the same image dataset. As before, for each image two values of D (note that $D = D_2$ in this condition) and $\bar{D}_m$ will be obtained. According to the decision rule in (1), if $\bar{D}_m \geq D$, the test image will correctly predicted as a doubly compressed image. Otherwise, a wrong decision will be made. The probability that the doubly compressed image has been correctly predicted is represented by TPR.
3) The final detection AR corresponding to the modified ratio is computed as $(\mathrm{TNR} + \mathrm{TPR})/2$.

The detection results corresponding to different modified ratios are shown in Fig. 4. Note that in all our testing, the parameter k, i.e., the repeated times k in Step 4 of our detection algorithm is selected as 5. Generally, with a bigger value k, a smoother AR curve will be obtained. In Fig. 4, the horizontal axis is the modified ratio (represented by $mpnc$), and the vertical axis represents the corresponding detection accuracy rate.

TABLE II
AR-HIGHEST RATIO AND ITS AR-HIGHEST VALUES FOR DIFFERENT IMAGE DATASETS (AR IS THE MAXIMUM DETECTION ACCURACY RATE OBTAINED AND $mpnc$ IS THE CORRESPONDING MODIFIED RATIO OF JPEG COEFFICIENTS)

QF	UCID		NRCS		OurLab		Composite Dataset	
	mpnc	*AR*	*mpnc*	*AR*	*mpnc*	*AR*	*mpnc*	*AR*
70	0.013	73.65	0.015	69.21	0.010	66.40	0.015	69.63
75	0.015	75.00	0.016	72.29	0.013	69.41	0.015	72.08
80	0.018	85.80	0.020	78.84	0.017	76.37	0.020	80.31
85	0.020	87.89	0.025	79.75	0.017	75.98	0.021	80.97
90	0.020	92.41	0.024	96.18	0.018	92.95	0.020	93.70
95	0.023	99.14	0.023~0.030	99.97	0.019~0.022	100	0.023	99.69
100	0.017~0.027	100	0.015~0.028	100	0.013~0.027	100	0.017~0.027	100

TABLE III
CROSS DETECTION ACCURACY RATES FOR DIFFERENT IMAGE DATASETS (THE DETECTION RESULTS WITH UNDERLINE REPRESENT THIS CASE. THE DIFFERENCE BETWEEN THE CROSS DETECTION ACCURACY RATE AND THE CORRESPONDING AR-HIGHEST VALUE OBTAINED FROM THE SAME IMAGE DATASET IS LESS THAN 1%)

QF	*AR*-highest ratio of UCID			*AR*-highest ratio of NRCS			*AR*-highest ratio of OurLab			*AR*-highest ratio of Composited Dataset			
	mpnc	NRCS	OurLab	*mpnc*	UCID	OurLab	*mpnc*	UCID	NRCS	*mpnc*	UCID	NRCS	OurLab
70	0.013	**68.63**	65.12	**0.015**	**73.51**	**65.60**	0.010	72.12	**68.63**	0.015	**73.51**	**69.21**	**65.60**
75	0.015	**72.00**	**68.71**	**0.016**	**74.36**	**69.06**	0.013	**74.66**	**71.84**	0.015	**75.00**	**72.00**	**68.71**
80	0.018	**78.54**	**75.93**	**0.020**	**85.54**	**76.11**	0.017	**85.20**	**78.48**	0.020	**85.54**	**78.84**	**76.11**
85	0.020	**79.29**	74.82	**0.025**	86.77	73.80	0.017	86.73	77.80	0.021	**87.74**	**79.33**	**75.18**
90	0.020	**95.78**	**92.38**	**0.024**	**91.70**	90.03	0.018	**91.48**	95.07	0.020	**92.41**	**95.79**	**92.38**
95	0.023	**99.97**	**99.96**	**0.026**	**98.99**	**99.91**	0.020	**98.62**	**99.81**	0.023	**99.14**	**99.97**	**99.96**
100	0.022	**100**	**100**	**0.021**	**100**	**100**	0.020	**100**	**100**	0.023	**100**	**100**	**100**

The blue solid curve with upward-pointing triangle markers, the red dotted curve with downward-pointing triangle markers, and the green dashed–dotted curve with plus sign markers represent the detection accuracy rates obtained from the image datasets of UCID, NRCS, and OurLab, respectively. From experimental results in Fig. 4, we can fix the maximum AR values and their corresponding "proper" ratios for different image datasets. For simplicity, the obtained maximum AR values and its corresponding "proper" ratios in these image datasets are referred as AR-highest value and AR-highest ratio, respectively.

It is observed from Fig. 4 that for the images with the same QF, the achieved AR curves corresponding to different image datasets have the similar variation tendency. The AR-highest ratio almost has nothing to do with the image dataset, and is only dependent on the image QF. That is to say, the AR-highest ratio that we have found in any image dataset may also work on the other two image datasets, and hence is universal in these three image datasets. Furthermore, since the AR curve is continuously changed, the adjacent point near the AR-highest ratio point can also achieve reliable detection performance. For example, in Fig. 4(a), the AR-highest ratio of NRCS with QF 70 is at the point 0.015, and the corresponding AR-highest value is 69.21. We can find that at the adjacent point 0.010, the detection accuracy rate obtained is 68.63, which is similar to the AR-highest value that can be achieved. It is noted that the point 0.010 is the AR-highest ratio for OurLab image dataset with QF $= 70$. Namely, even if we cannot find the AR-highest ratio accurately, a suboptimum "proper" ratio still does work.

In Table II, the AR-highest values and the corresponding AR-highest ratios for all the three image datasets and the composite image dataset (i.e., the three image datasets are combined together) are illustrated, where the AR-highest ratio is represented by $mpnc$ value. It is observed from Table II that although the best detection accuracy rates for different image datasets are somehow different, the corresponding AR-highest ratios are in the similar regions. Especially when the QF is 100, the AR-highest ratio for any image dataset can be selected in a wide range, and these AR-highest ratio ranges corresponding to the different image datasets are overlapped. That is, for all these image datasets, the same AR-highest ratio can be selected to achieve the best detection accuracy rate when QF is 100. Moreover, we can find that if the QF is no less than 90, the final detection accuracy rates are constantly higher than 90% for any image dataset. While the QF is as high as 100, the AR-highest values that can be achieved are constantly 100%.

B. Cross Detection Results

In order to further demonstrate the universality of AR-highest ratios obtained from the aforementioned three image datasets, we also use them to make a cross detection. That is, the AR-highest ratio obtained from any one of three image datasets is used to test the images in the other two image datasets. Finally, we also use the AR-highest ratio obtained from the composite datasets to test the images in UCID, NRCS, and OurLab, respectively. The experimental results are shown in Table III. Note that when the AR-highest ratio has multiple values, we choose the median value for testing. For example, as to the UCID image dataset with QF $= 100$, the AR-highest ratio can be chosen in a wide range $[0.017, 0.027]$. In our experiments, we choose the median value 0.022 for testing. In Table III, the detection results with underline represent that in this case, the difference between the cross detection accuracy rate and the corresponding AR-highest value obtained from the same image dataset in Table II is less than 1%. It is observed that in most cases the cross detection accuracy rates are close to the corresponding AR-highest value that can be achieved in

TABLE IV
DETECTION RESULTS OF TRIPLE JPEG COMPRESSION (AR IS THE MAXIMUM DETECTION ACCURACY RATE OBTAINED AND $mpnc$ IS THE CORRESPONDING MODIFIED RATIO OF JPEG COEFFICIENTS)

QF	Single-Triple		Double-Triple	
	mpnc	*AR*	*mpnc*	*AR*
70	0.006	81.39	0.004	67.08
75	0.009	82.84	0.005	67.75
80	0.012	91.59	0.005	66.70
85	0.014	92.89	0.007	67.12
90	0.015	96.26	0.007	67.85
95	0.007~0.016	100	0.006	99.03
100	0.008~0.027	100	0.008	99.93

Table II. The maximum difference between the cross detection accuracy rate and the corresponding AR-highest value is no more than 2.92% in all our testing. The cross detection results also demonstrate that if the QF is no less than 90, the final detection accuracy rates are constantly higher than 90%. While the QF is as high as 100, the detection accuracy rates that can be achieved are 100%.

As seen, the AR-highest ratio obtained from any image dataset still works for the other two image datasets, and thus is universal in these three image datasets.

C. Detection of Triple JPEG Compression

Here, we give some experiments to demonstrate the potentiality that our proposed method can also be used to detect the triple JPEG compression with the same quantization matrix. There are two types of binary classifiers. The first one is used for discriminating the singly compressed image from the triply compressed image, and the second one is used to discriminate the doubly compressed image from the triply compressed image. For simplicity, we only illustrate the experimental results about the UCID image dataset. The experimental results are shown in Table IV. As we can see, since the number of different JPEG coefficients between the singly compressed image and the triply compressed image is generally much larger than the number of different JPEG coefficients between the doubly compressed image and the triply compressed image, which has been shown in Fig. 3, the doubly compressed image and triply compressed image will be more difficult to be discriminated. However, when the QF is as high as 95, it is observed from Table IV that the doubly compressed image and triply compressed image can still be discriminated reliably using our proposed method.

D. Discussions

From the above experiments, we can find out that the final detection accuracy rates of our proposed double JPEG compression detection algorithm have a very close relation to the QF of the test image. Generally, with a higher QF, the final detection result will be more reliable. Some explanation can be found in Table I. As seen, with the decreasing of QF, the number of different JPEG coefficients between the singly compressed image and doubly compressed image are becoming smaller generally. The major reason is that for JPEG compression, the quantization steps corresponding to lower QFs are bigger than that corresponding to higher QFs. Thus, with the decreasing of QF, the modification to JPEG coefficients which are introduced by the aforementioned three kinds of errors in JPEG compression and decompression process will become less. We can imagine that with the decreasing of QF, the detection accuracy rates of our proposed method will become lower and lower and even do not work.

However, when the QF is no less than 70, our extensive experiments on three different image datasets demonstrate that the difference between the singly compressed image and doubly compressed image can be discriminated, especially when the QF is as high as 90, a very reliable detection accuracy rate can be obtained. Most importantly, the "proper" ratios obtained from all three image datasets are universal. The cross detection results exemplified in Table III demonstrate that the AR-highest ratio obtained in any image dataset also does work on the other two image datasets. It follows that we can also utilize the AR-highest ratios obtained from the three image datasets to test other unknown images. For example, for unknown JPEG images with QF $= 70$ (note that the QF value can be read from the head file of the JPEG image), according to the experimental results in Table II, we can select the "proper" ratios as 0.015 to determine whether it is doubly compressed. As we know, images are complicated. Why can a constant "proper" ratio be utilized for detecting the images with different properties? Before answering this question, we give an explanation of the philosophy behind our algorithm first. Without loss of generality, we suppose the JPEG images to be tested are with QF $= 80$. According to Step 1 of our proposed method, the test images are recompressed again with the same QF, and a value D can be obtained, which represents the number of different JPEG coefficients between the test image and the recompressed image. Note that for different images, the values of D are different because of their different properties. Then we randomly modified a "proper" ratio of JPEG coefficients of the recompressed image as described in Steps 2–4 to find the $\bar{D}_m$, which is adopted as a threshold. Through comparing $\bar{D}_m$ with D, whether the test image is doubly compressed can be determined. It is noted that for all the test images with the same QF, the "proper" ratio being utilized may be the same. However, the values of $\bar{D}_m$ are not constant for different images. It is dynamically changed according to the properties of the test image. Namely, in our method, we have utilized a dynamical threshold value $\bar{D}_m$ to discriminate the singly compressed image and doubly compressed image. That is the major reason why in our method a universal "proper" modification ratio does work.

IV. CONCLUSION

Because the difference between the singly compressed JPEG image and doubly compressed JPEG image with the same quantization matrix is small, detection of double JPEG compression with the same quantization matrix is a challenging problem. To the best of our knowledge, no method which can detect such a case has been reported in the literature. In this paper, we have presented a method to detect it. Through a random perturbation strategy, the difference between a singly compressed image and a doubly compressed image can be discriminated, especially when the image is compressed with relatively high QF.

As mentioned above, reliable detection of double JPEG compression with the same quantization matrix is quite important in the field of digital forensics. Our new method may have some applications. For example, if the steganographer is smart enough, they can choose to generate the stego image with the same QF as that of the cover image. The forgery maker can also choose to recompress the composite image with the same quantization matrix as that of the source or target image to avoid the abnormal properties such as "missing values" and "double peak" which may exist in the forgery image. Thus the previous double JPEG compression detection method may not work. However, the traces of double JPEG compression still exist, and our algorithm can be used to detect it.

It is noted that our proposed method is not limited to detection of double JPEG compression. It can also be extended to detect the triple JPEG compression, four times JPEG compression, and so on. As stated above, the key issue is still the "proper" ratio that we should find.

REFERENCES

[1] J. Lukáš and J. Fridrich, "Estimation of primary quantization matrix in double compressed JPEG images," in *Proc. Digital Forensic Research Workshop*, Cleveland, OH, Aug. 2003.

[2] T. Pevný and J. Fridrich, "Detection of double-compression in JPEG images for applications in steganography," *IEEE Trans. Inf. Forensics Security*, vol. 3, no. 2, pp. 247–258, Jun. 2008.

[3] H. Farid, "Exposing digital forgeries from JPEG ghosts," *IEEE Trans. Inf. Forensics Security*, vol. 4, no. 1, pp. 154–160, Mar. 2009.

[4] Z. Lin, J. He, X. Tang, and C. -K. Tang, "Fast, automatic and fine-grained tampered JPEG image detection via DCT coefficient analysis," *Pattern Recognit.*, vol. 42, pp. 2492–2501, 2009.

[5] A. Westfeld, "High capacity despite better steganalysis (F5-A steganographic algorithm)," in *Proc. 4th Int. Workshop Information Hiding*, 2001, vol. 2137, pp. 289–302, Lecture Notes in Computer Science.

[6] N. Provos, "Defending against statistical steganalysis," in *Proc. 10th USENIX Security Symp.*, Washington, DC, 2001.

[7] R. Yang, Y. Q. Shi, and J. Huang, "Defeating fake-quality MP3," in *Porc. ACM Multimedia and Security'09*, Princeton, NJ, Sep. 7–8, 2009.

[8] W. Wang and H. Farid, "Exposing digital forgeris in video by detecting double MPEG compression," in *Porc. ACM Multimedia and Security'06*, Geneva, Switzerland, Sep. 26–27, 2006.

[9] W. Wang and H. Farid, "Exposing digital forensics in video by detecting double quantization," in *Proc. ACM Multimedia and Security'09*, Princeton, NJ, Sep. 7–8, 2009.

[10] A. C. Popescu, "Statistical Tools for Digital Image Forensics," Ph. D., Department of Computer Science, Dartmouth College, Hanover, NH, 2004.

[11] A. C. Popescu and H. Farid, "Statistical tools for digital forensics," in *Proc. 6th Int. Workshop on Information Hiding*, 2004, vol. 3200, pp. 128–147, Lecture Notes in Computer Science.

[12] D. Fu, Y. Q. Shi, and W. Su, "A generalized Benford's law for JPEG coefficients and its applications in image forensics," in *Proc. SPIE, Security, Steganography and Watermarking of Multimedia Contents IX*, San Jose, CA, Jan. 2007.

[13] B. Li, Y. Q. Shi, and J. Huang, "Detecting double compressed JPEG images by using mode based first digit features," in *Proc. IEEE Int. Workshop on Multimedia Signal Processing (MMSP 2008)*, Cairns, Queensland, Australia, Oct. 8–10, 2008.

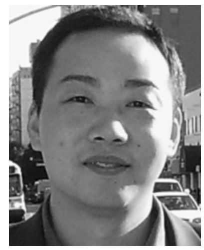
[14] C. Chen, Y. Q. Shi, and W. Su, "A marching learning based scheme for double JPEG compression detection," in *Proc. IEEE Int. Conf. Pattern Recognition*, Tampa, FL, Dec. 8–11, 2008.

[15] G. K. Wallace, "The JPEG still picture compression standard," *IEEE Trans. Consumer Electron.*, vol. 38, no. 1, pp. XVIII–XXXIV, Feb. 1992.

[16] G. Schaefer and M. Stich, UCID—An Uncompressed Colour Image Database School of Computing and Mathematics, Nottingham Trent University, U.K., 2003.

[17] NRCS Photo Gallery [Online]. Available: http://photogallery.nrcs.usda.gov

[18] JPEG Tool Box [Online]. Available: http://www.philsallee.com/jpegtbx/index.html



Fangjun Huang (M'07) received the B.S. degree from Nanjing University of Science and Technology, China, in 1995, and the M.S. and Ph.D. degrees from Huazhong University of Science and Technology, China, in 2002 and 2005, respectively.

Since 2005, he is with the School of Information Science and Technology, Sun Yat-Sen University, Guangzhou, China. From June of 2009 to June of 2010, he was also a postdoctoral researcher in Department of Electrical and Computer Engineering, New Jersey Institute of Technology, Newark, NJ. His research interests include digital forensics and multimedia security.

Jiwu Huang (M'98–SM'00) received the B.S. degree from Xidian University, China, in 1982, the M.S. degree from Tsinghua University, China, in 1987, and the Ph.D. degree from the Institute of Automation, Chinese Academy of Science, in 1998.

He is currently a professor with the School of Information Science and Technology, Sun Yat-Sen University, Guangzhou, China. His current research interests include multimedia forensics and security.

Dr. Huang received the China National Funds for Distinguished Young Scientists from the NSF of China in 2003. He received the first-grade award in science research from the National Ministry of Education, China, in 2004. He and his students won the best student paper award in the 8th International Workshop on Digital Watermarking (Pusan, Korea) in 2008. He has served as a technical program committee member for many international conferences. He serves as a member of IEEE CAS Society Technical Committee of Multimedia Systems and Applications. He is an Associate Editor for IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, *LNCS Transactions on Data Hiding and Multimedia Security* (Springer), and *EURASIP Journal on Information Security* (Hindawi).

Yun Qing Shi (M'88–SM'92–F'05) received the B.S. and M.S. degrees from Shanghai Jiao Tong University, Shanghai, China, and the M.S. and Ph.D. degrees from University of Pittsburgh, PA.

He joined Department of Electrical and Computer Engineering at New Jersey Institute of Technology, Newark, NJ, in 1987, and is now a professor there. His research interests include digital multimedia data hiding, steganaysis, forensics and information assurance, visual signal processing and communications, motion analysis, theory of multidimensional systems, and signal processing. He is an author/coauthor of more than 200 papers, a book, and five book chapters. He holds nine awarded U.S. patents and has an additional 20 U.S. patents pending.

He is the Editor-in-Chief of *LNCS Transactions on Data Hiding and Multimedia Security* (Springer) and an Associate Editor of the *Journal on Multidimensional Systems and Signal Processing* (Springer). He served as an Associate Editor of IEEE TRANSACTIONS ON SIGNAL PROCESSING (1994–1996) and IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS II (2004–2005), a member of the editorial board of the *International Journal of Image and Graphics* (1999–2007), a guest editor of special issues for a few journals, an IEEE CASS Distinguished Lecturer (2002–2003), the technical program chair of ICME07, cotechnical chair of IWDW06, 07, 09, and MMSP05, and the cogeneral chair of MMSP02. He is a member of a few IEEE technical committees, and a Fellow of IEEE for his contribution to Multidimensional Signal Processing.