DISCRIMINATING MULTIPLE JPEG COMPRESSION USING FIRST DIGIT FEATURES

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ABSTRACT

The analysis of double-compressed images is a problem largely studied by the multimedia forensics community, as it might be exploited, e.g., for tampering localization or source device identification. In many practical scenarios, e.g. photos uploaded on blogs, on-line albums, and photo sharing web sites, images might be compressed several times. However, the identification of the number of compression stages applied to an image remains an open issue. This paper proposes a forensic method based on the analysis of the distribution of the first significant digits of DCT coefficients, which is modeled according to Benford's law. The method relies on a set of Support Vector Machine (SVM) classifiers and allows us to accurately identify the number of compression stages applied to an image. Up to four consecutive compression stages were considered in the experimental validation. The proposed approach extends and outperforms the previously published methods aimed at detecting double JPEG compression.

Index Terms— multiple JPEG compression, forgery identification, first digit features, Benford's law.

1. INTRODUCTION

Multimedia forensic analysts have recently considered the possibility of identifying images which has been compressed more than once and reconstructing the coding parameters of the previous coding stages. In principle, image compression can be performed an arbitrary number of times. However, most of the solutions proposed in the literature limit their analysis to the case of double compression, i.e., they aim at detecting whether an image has been compressed once or twice. However, we believe that this assumption does not hold in many practical scenarios, since images might be compressed several times, and possibly edited between two consecutive compression stages. As an illustrative example, let us consider an image, which is originally compressed by the acquisition device (i.e., a video or photo camera) to be stored in the onboard memory. A second compression is performed by the owner, after editing the image to enhance the perceptual quality and adjust the format (e.g., brightness/contrast adjustment, rescaling, cropping, color correction, etc.). A third compression is performed whenever the content is uploaded to a blog or to an on-line photo album. As a matter of fact, it is reasonable to assume that a large number of digital images available on-line have gone through more than two compression stages performed by its owner, and could be further compressed by other users. In these cases, a method that identifies the number of compression stages proves to be extremely important in reconstructing the processing history.

In this paper, we focus on images compressed by means of JPEG [1] since it is by far the most widely adopted compression standard. As mentioned before, previous works focused on the detection of double JPEG compression, assuming that an image was coded once or twice. Some of the proposed solutions analyze of the statistics of DCT coefficients [2]. Other strategies rely on the assumption that quantization is an idempotent operation, i.e., requantizing DCT coefficients with the same quantizer leads to reconstructed values highly-correlated with its input [3]. In [4], the authors detect double compression by studying coding artifacts. Other methods rely on characterizing the statistics of natural images. These include the approaches based on the analysis of the distribution of the first significant digits, which can be modeled according to Benford's law [5].

Similarly to [5], in our investigation we study how DCT coefficient statistics change when an image goes through several compression stages. More precisely, our analysis considers the most significant decimal digit or first digit (FD) of DCT coefficient absolute values. We propose a method based on a set of Support Vector Machine (SVM) classifiers, which permits estimating the number of coding cycles. Experimental results show that it is indeed possible to infer the number of compression stages from the FD statistics with a reasonable approximation.

The proposed technique can be employed in different application scenarios, including steganalysis [2], detection of image manipulation (when the original image is decompressed, modified, and recompressed), forgery identification [6], and quality assessment.

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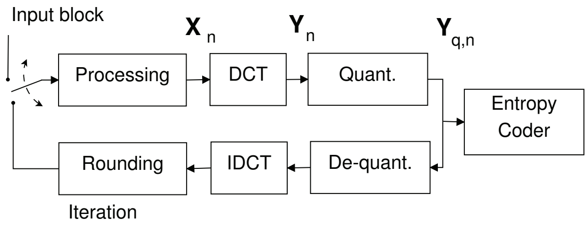


Fig. 1. Bock diagram for multiple JPEG compression.

In the following, Section 2 describes the behavior of DCT coefficient statistics, as they go through multiple quantization stages, while Section 3 presents the proposed classification method. Experimental results are reported in Section 4 and final conclusions are drawn in Section 5.

2. MULTIPLE COMPRESSIONS AND COEFFICIENTS STATISTICS

The JPEG image compression standard defines a block-based transform coder (see Fig. 1), which partitions the input image into 8×8 pixel blocks $\mathbf{X}$ and computes the Discrete Cosine Transform (DCT) of each block. Transform coefficients $\mathbf{Y}$ are quantized into integer-valued quantization levels $\mathbf{Y}_{q_1}$

$$Y_{q_1}(i,j) = \text{sign}(Y(i,j))\text{round}\left(\frac{|Y(i,j)|}{q_1(i,j)}\right), \quad (1)$$

where the indexes (i, j) denote the position of the elements in the 8×8 block. The values $Y_{q_1}(i, j)$ are converted into a binary stream by an entropy coder following a zig-zag scan that orders coefficients according to increasing spatial frequencies. The coded block can be reconstructed by applying an inverse DCT transform on the rescaled coefficients $Y_{q_1}(i, j) \cdot q_1(i, j)$. Note that the quantization step $q_1(i, j)$ changes according to the index (i, j) of the DCT coefficient and is usually defined by means of a quantization matrix. In the IJG (Independent JPEG Group) implementation, the quantization matrix is selected by adjusting a quality factor (QF), which varies in the range $[0, 100]$. The higher QF, the higher the quality of the constructed image.

When the image is encoded a second time, the resulting quantization levels are

$$Y_{q_2}(i,j) = \text{sign}(Y_{q_2}(i,j))\text{round}\left(\frac{|Y_{q_1}(i,j) \cdot q_1(i,j)|}{q_2(i,j)}\right), \quad (2)$$

where $q_2(i, j)$ are the quantization steps of the second compression stage.[1] It is possible to iterate the compression process N times leading to the quantization levels $Y_{q_N}(i, j)$.

[1]Note that in this model we omit to consider the rounding and clipping of the reconstructed pixels to finite precision integer values after inverse DCT. This approximation is allowed by the fact that the effects of quantization prevail over those of rounding.

In order to detect double JPEG compression from the pixel values of an image, some of the approaches proposed in the literature [5] rely on detecting the violation of the so-called Benford's law (also known as first digit law or significant digit law). Let m denote the first digit (FD) m, i.e.

$$m = \left\lfloor \frac{|Y(i,j)|}{10^{\lfloor \log_{10} |Y(i,j)| \rfloor}} \right\rfloor. \quad (3)$$

It has been observed that the empirical probability mass function (pmf) $\hat{p}(m)$ of m follows the generalized equation

$$p(m) = K \log_{10}\left(1 + \frac{1}{\alpha + m^\beta}\right), \text{ with } m = 1, \dots, 9. \quad (4)$$

After quantization, the pmf $\hat{p}(m)$ computed from $Y_{q_1}(i, j)$ deviates from $p(m)$ as defined in eq. (4). According to the characteristics of such deviation, it is possible to detect whether m has been generated from $Y_{q_1}(i, j)$ or $Y_{q_2}(i, j)$.

However, these solutions aim at detecting whether an image has been coded once or twice. In the case of images that have gone through multiple compression stages, these strategies fail in discriminating the number of coding stages and the corresponding coding parameters.

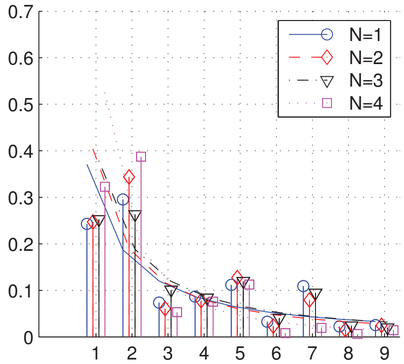
This is due to the large number of possible configurations and to the amount of noise introduced on the coefficients by each quantization step. Figure 2 reports the pmf of the FD for the quantized DCT coefficients of frame 0 in the sequence `foreman`, for different numbers of compression stages. It is possible to notice that, as the number of stages increases, the pmf becomes less regular. As a matter of fact, it is necessary to identify a robust set of parameters that can be used to detect the number of coding stages.

3. THE PROPOSED DETECTION ALGORITHM

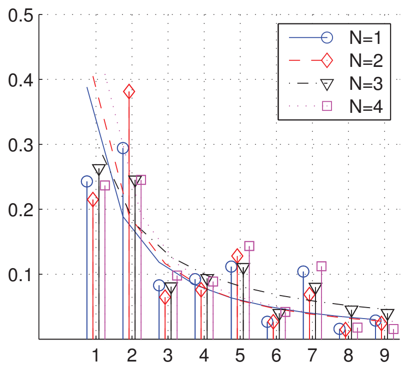
The estimation of the number of coding stages N requires selecting a set of robust features that presents a strong correlation with the traces left by quantization. Previous works relied on the analysis of the pmf of the FD m for a subset of spatial frequencies. In [5], 20 spatial frequencies were considered, leading to feature vectors of 180 elements. Other approaches considered the relative difference between the actual pmf and the Benford's equation, i.e. $\chi(m) = (p(m) - \hat{p}(m))/\hat{p}(m)$ [7].

In our approach, we aim at reducing the size of the feature vectors by properly selecting those features that are extremely sensible to the number of compression stages. More precisely, Fig. 2 shows that the probabilities for some FD values are more sensitive to multiple compression than others, i.e., the deviation from Benford's law equation is more discriminative.

More precisely, our approach considers only the coefficients at 9 different spatial frequencies (defined in [2]) and computes, for each of them, the pmf $\hat{p}(m)$ of the FD. Then, a classifier processes, per each transform coefficient, a subset of



(a) coefficient at $(0, 0)$.



(a) coefficient at $(0, 1)$.

Fig. 2. Probability mass functions of FD m and their relatives Benford's models at different coding stages. The graphs are related to coefficients at different spatial frequencies.

the pmf values corresponding to three digits, i.e. $m = 2, 5, 7$, since in our experiments these proved to be the ones that vary the most as functions of the compression stages.

As a results, each image is represented with a feature vector $\mathbf{v}$ of 27 elements (i.e. approximately 6 times smaller than in [5]).

Given the quality factor of the last compression stage, which can be extracted from the available bitstream, it is possible to build a set of N_T binary SVM classifiers, $\mathcal{S}_k$ ($k = 1, \ldots, N_T$). Each classifier $\mathcal{S}_k$ is able to detect whether the input image has been coded k-times or not.

In designing $\mathcal{S}_k$, we adopted the logarithmic kernel

$$K(\mathbf{v}_i, \mathbf{v}_j) = -\log\left(\|\mathbf{v}_i - \mathbf{v}_j\|_2^{\gamma_k} + 1\right), \quad (5)$$

where the parameter γ_k is found in the training phase. Each classifier also outputs a confidence value ξ_k that reports the distance from the secant hyperplane (related to slack variables) and permits evaluating the reliability of the classification. This value is employed to compute a multiclass confidence value

$$\Xi_k = \sum_{\forall h=1, h\neq k}^{N_T} \mathcal{I}(\xi_h < 0)\,|\xi_h| + \mathcal{I}(\xi_k > 0)\,|\xi_k|, \quad (6)$$

where $\mathcal{I}(\cdot)$ is the indicating function. Finally, the algorithm estimates that the image has been coded $N^* = \arg\max_N \Xi_N$ times.

4. EXPERIMENTAL RESULTS

In order to evaluate the accuracy of the proposed classifier, we randomly selected 20 images to train $\mathcal{S}_k$ and the remaining 1308 images (in the complementary set) for testing from the UCID dataset [8]. At each compression stage, the quality factor QF was sampled from a random variable uniformly distributed in the interval $[QF_N - 10, QF_N + 10]$, where QF_N is the quality factor of the last compression stage. In our tests we adopted $QF_N \in \{70, 75, 80, 85, 90\}$ (we only reports the results for $QF_N = 75$ for the sake of conciseness). This assumption is reasonable, since strong variations in QF across the different compression stages would lead to severe quality degradation that would make the resulting image useless. Moreover, we also imposed that the QFs between two consecutive compression stages must differ by at least 3 units. In this way, we avoided the trivial case in which an image is recompressed with the same QF. In the testing phase, 10 different realizations (chains of random QFs for each compression stage) were generated for each image and each QF_N value.

Table 1a reports the confusion matrix obtained with the proposed method. It is possible to notice that the case of a single compression stage is always correctly identified. In the case an image was compressed 2 or 3 times, the proposed method performs quite well since the probability of correct detection is above 96 %. We compare the performance with that of a classifier designed adapting the work in [5] in order to detect the number of compression stages. The confusion matrix, which is shown in Table 1b, demonstrates that the two methods achieve nearly the same results for $N \leq 3$. However, the proposed method is characterized by a lower computational complexity, since the size of the feature vector is much smaller. When $N = 4$, the accuracy of the proposed solution slightly decreases, allowing us to correctly detect the number of compression stages in approximately 94 % of the cases. Conversely, the method adapted from [5] achieves a probability of correct detection equal to 87 %. This performance loss is due to the difficulty in identifying an adequate set of support vectors, because of the high dimensionality of feature vectors and the increased amount of noise introduced by multiple compressions.

Furthermore, we also tested the robustness of the approach in case an image is manipulated between consecutive compression stages. More precisely, we assumed that image manipulation took place at the processing block in Fig. 1, before the last coding stage. At first, we tested our approach in presence of rescaling before the last coding stage, i.e., the image size was (up/down)scaled and then brought back to its original dimensions with the introduction of aliasing

Table 1. Confusion matrix for $QF_N = 75$.
a) proposed method b) classifier in [5].

N , N*	1	2	3	4
1	100.00 %	0.00 %	0.00 %	0.00 %
2	0.00 %	100 %	0.00 %	0.00 %
3	0.00 %	3.57 %	96.43 %	0.00 %
4	3.57 %	1.79 %	0.00 %	94.64 %

(a)

N , N*	1	2	3	4
1	100 %	0.00 %	0.00 %	0.00 %
2	1.79 %	98.21 %	0.00 %	0.00 %
3	0.00 %	0.00 %	100.00 %	0.00 %
4	12.50 %	0.00 %	0.00 %	87.50 %

(b)

Table 2. Confusion matrix for $QF_N = 75$ with rescalings.
a) proposed method b) classifier in [5]

N , N*	1	2	3	4
1	100.00 %	0.00 %	0.00 %	0.00 %
2	0.00 %	100.00 %	0.00 %	0.00 %
3	1.02 %	0.00 %	98.98 %	0.00 %
4	94.90 %	0.00 %	0.00 %	5.10 %

(a)

N , N*	1	2	3	4
1	100.00 %	0.00 %	0.00 %	0.00 %
2	0.00 %	100.00 %	0.00 %	0.00 %
3	1.02 %	0.00 %	98.98 %	0.00 %
4	35.71 %	0.00 %	0.00 %	64.29 %

(b)

noise due to non-ideal interpolation. The rescaling factor was sampled from a random variable uniformly distributed in the range $[0.5, 2.0]$. Results in Table 2 show that the proposed classifier (trained on non-rescaled images) proves to be robust up to 3 compression stages. Note also that increasing the size of the feature vector $\mathbf{v}$ does not bring any improvement in terms of performance.

Finally, we tested the robustness of the proposed approach to rotation and cropping (see Table 3). In this case, the rotation angle is sampled from a uniform random variable in the interval $[-30, 30]$. Experimental results show that the proposed approach is robust up to 3 compression stages.

5. CONCLUSIONS

The paper describes a classification strategy that permits detecting the number of JPEG compression stages performed on a single image. The approach relies on a set of SVM classifiers applied to features based on the statistics of the first digits of quantized DCT coefficients. The proposed solution performs well with respect to previous approaches, while employing a reduced set of features. Moreover, it proves to be robust in presence of image manipulations (scaling, rotation/cropping) between two consecutive compression stages. Future research will be devoted to investigate other possible antiforensics strategies that could fool the proposed solution and to extend the approach to the case of video signals.

Table 3. Confusion matrix for $QF_N = 75$ with rotations.
a) proposed method b) classifier in [5]

N , N*	1	2	3	4
1	100.00 %	0.00 %	0.00 %	0.00 %
2	0.00 %	100.00 %	0.00 %	0.00 %
3	2.04 %	0.00 %	97.96 %	0.00 %
4	96.94 %	0.00 %	3.06 %	5.10 %

(a)

N , N*	1	2	3	4
1	100.00 %	0.00 %	0.00 %	0.00 %
2	0.00 %	100.00 %	0.00 %	0.00 %
3	1.02 %	0.00 %	98.98 %	0.00 %
4	45.92 %	0.00 %	0.00 %	54.08 %

(b)

6. REFERENCES

[1] G.K. Wallace, "The JPEG still picture compression standard," *IEEE Trans. Consum. Electron.*, vol. 38, no. 1, pp. xviii –xxxiv, feb 1992.

[2] T. Pevny and J. Fridrich, "Estimation of primary quantization matrix for steganalysis of double-compressed JPEG images," in *Proc. of SPIE*, San Jose, CA, USA, Jan. 2008, vol. 6819, pp. 11–1 – 11–13.

[3] M. Xian-Zhe, N. Shao-Zhang, and Z. Jian-Chen, "Tamper detection for shifted double JPEG compression," in *Proc.of IIH-MSP 2010*, Darmstadt, Germany, Oct. 2010, pp. 434 –437.

[4] M. Barni, A. Costanzo, and L. Sabatini, "Identification of cut & paste tampering by means of double-JPEG detection and image segmentation," in *Proc. of ISCAS 2010*, Paris, France, May 30–June 2, 2010, pp. 1687–1690.

[5] B. Li, Y. Q. Shi, and J. Huang, "Detecting doubly compressed JPEG images by using mode based first digit features," in *Proc. of MMSP 2008*, Cairns, Queensland, Australia, Oct. 2008, pp. 730–735.

[6] W. Wang and H. Farid, "Exposing digital forgeries in video by detecting double MPEG compression," in *Proc. of ACM MM&Sec 2006*, Geneva, Switzerland, Sept. 2006, pp. 37–47.

[7] D. Fu, Y. Q. Shi, and W. Su, "A generalized Benfords law for JPEG coefficients and its applications in image forensics," in *Proc. of SPIE*, Jan. 28 – Feb. 1, 2009, vol. 6505, pp. 39–48.

[8] G. Schaefer and M. Stich, "UCID - An uncompressed colour image database," in *Proc. SPIE*, San Jose, CA, USA, Jan. 2004, vol. 5307, pp. 472 – 480.