2016 IEEE 8th International Conference on Intelligent Systems

A Dictionary Based Approach to JPEG Anti-Forensics

Nasser Afshin, Farbod Razzazi
Department of Electrical and Computer Engineering
Science and Research Branch, Islamic Azad University
Tehran, Iran
Email: naser.afshin@srbiau.ac.ir, razzazi@srbiau.ac.ir

Mohammad-Shahram Moin
Iran Telecommunication
Research Center
Tehran, Iran
Email: moin@itrc.ac.ir

***Abstract*—JPEG compression is a common standard for storing images. Its intrinsic lossy compression scheme, helps forensic analysts to disclose the history of the image by analyzing the histogram of discrete cosine transform (DCT) coefficients. In this paper, we propose a novel method based on sparse representation of the image, over learned over-complete dictionaries to conceal the statistical evidences of forgeries in JPEG compressed images. We will show that the proposed algorithm successfully fools currently used forensic methods. So that some of the state-of-the-art forensic tools which have an average performance accuracy of more than %90, produce random guess results on our anti-forensically doctored images.**

***Keywords*—anti-forensics; sparse representation; k-singular value decomposition; orthogonal matching pursuit; total variation; JPEG; discrete cosine transform; over-complete dictionary**

I. Introduction

The widespread use of JPEG format for image compression and publication on the Internet and availability of image forgery softwares for everyone, decreased the trust on the image originality. This fact makes it very crucial to evaluate the validity of images to see if they are tampered in any way [1]. Forged images may be used for misleading the court, altering the society opinion about a fact and also propaganda. To restore the traditional trust on captured images, many forensic methods have been proposed. These passive methods do not rely on added watermark data [2] in the images, because there is no such extrinsic data on most of them. Instead image forensic analysts try to use intrinsic features of an image to evaluate its authenticity. As a common evidence, statistical traces of transform compression, make it easy to reveal the history of compressed images. Using forensic methods one can detect the camera which was used to capture the image also known as image ballistics [3], quantization matrix [4], copy-move forgeries [5] and also localized evidence of double compression of either aligned or nonaligned DJPEG [6]–[8].

As opposed to the forensic methods, hiding the traces of JPEG compression history is called anti-forensics. Anti-forensic algorithms try to conceal the footprints of image tampering. As an example, in [3], [9], [10] authors claimed that the JPEG quantization table is almost distinct across different camera manufacturers and therefore can be used as a key reference to confirm or deny an image source. By proper use of anti-forensic algorithms, a knowledgeable adversary can conceal the history of a software tampered image and makes it hard (if not impossible) to detect the compression quantization table and therefore the image authenticity.

In this paper we propose a novel method of concealing the traces of JPEG compression. Our work in anti-forensics will help forensic analysts to offer more robust algorithms in detecting doctored images.

A. JPEG Compression

JPEG is a popular compression algorithm which is widely used in digital photography. Without loss of generality, we talk about gray-scale JPEG compression throughout this paper. However the same principles may apply to colored images.

To compress an image in JPEG standard, it is first divided into B non-overlapping blocks of size 8×8 pixels each. Then the 2-D discrete cosine transform (DCT) of each block is computed and called ${X_i}^b, 1 \leq b \leq B, 1 \leq i \leq 64$ where ${X_i}^b$ denotes the i-th DCT coefficient of the b-th block. Then each DCT coefficient is quantized with a quantization step size of q_i. $Q = [q_i]_{8\times8}$ is called the quantization matrix and determines the quality of compression. The quantization process is the source of the lossy nature of JPEG compression. So each quantized DCT coefficient is calculated ${W_i}^b = round({X_i}^b/q_i)$. Due to the nature of the quantization matrix Q, most of high frequency components of $[{W_i}^b]_{8\times8}$ are zero. Finally each block is scanned in a zig-zag order and a lossless data compression (entropy coding) is applied to reduce the size of the block.

JPEG decompression is performed by applying these steps in the reverse order. First, the lossless data decompression is applied to each block to reproduce the quantized DCT coefficients $[{W_i}^b]_{8\times8}$. Then each block is restored $\tilde{X}_i^b = q_i {W_i}^b$. The restored DCT coefficients in this stage will not be the same as the original coefficients. They are integer multiple of the quantization step. Then the inverse DCT is applied and the result is rounded and truncated in the range $[0, 255]$. To restore the uncompressed image, all image patches are joined together [11].

B. JPEG Artifacts Forensics

The lossy nature of JPEG compression leaves some intrinsic footprints on spatial and transform domain in an image. At very low bit rates, these artifacts are annoyingly visible. In spatial domain, ringing artifact appears due to the quantization of high frequency DCT components whereas blocking artifact arises because of the coarse quantization of low frequency DCT components [12]. Also due to the pixel discontinuity across block boundaries, blocking artifact becomes evident in JPEG compressed images. Forensic analysts have used these artifacts to detect JPEG footprints. The authors in [13] have detected JPEG footprint using blocking inconsistency.

On the other hand, the dequantized DCT coefficients, $\tilde{X}_i^b$, are integer multiples of their respective quantization step size. This leads to estimation of the quantization table [4], using a method based on maximum likelihood estimation. By comparing the quantizer table with a database of known quantization tables, authors of [3] have detected the camera model or software used in JPEG compression. Furthermore, when the matched table is of an editing software, the legitimacy of the image is vague. Authors of [14] have developed methods for detecting JPEG compression, JPEG quantization steps and also JPEG quantization table which perform well especially for the small size images. Lai and Böhme in their paper [15], proposed a forensic method based on the idea of calibration from steganalysis. They could successfully defeat the proposed method in Stamm et al.'s paper [16]. In [17], authors attempted to eliminate the JPEG blocking artifacts using a variational energy minimization method. Li et al. [18] have proposed a machine learning approach using steganalysis methods. A 100-dimensional feature vector has been extracted and fed to a Support Vector Machine (SVM) classifier which detects JPEG forgery. Authors of [19], introduced another machine learning approach based on Subtractive Pixel Adjacency Matrix (SPAM) feature vectors to detect JPEG footprints. Valenzise et al. [11] have applied a total variation based method to detect traces of JPEG compression and achieved a good performance.

Evidences of double-JPEG compression have also been detected [4], [6], [20]–[22]. Moreover, detection of localized evidence of double-JPEG compression [5], [23]–[26], is a good sign of copy-move forgeries.

C. JPEG Artifacts Anti-Forensics

Stamm et al. in [16] have proposed an algorithm to hide the traces of JPEG compression. The proposed method in [16] was essentially based on adding a dithering noise in the DCT domain to fill in the gaps in the DCT histogram of a JPEG image, and hiding the comb shape footprints. To fill the gaps in DCT coefficient histogram, the distribution of an image's DCT coefficients has been estimated [27]. Then the anti-forensic dithering noise has been sampled from those distributions and has been added to the DCT signal. Of course the result is an image with visual grainy noise. Anyway, using this method, has its own footprint and has been discovered by the authors of [11] and [15]. The detection in [11] has been performed by re-quantization of the DCT coefficients by various quality factors (Q_A), according to Fig. 1 and computing its total variation [28]. It has been shown that an abrupt fluctuation in TV versus Q_A diagram is the sign of a tampered image. Then some detectors has been proposed to detect this abrupt change. Our proposed method is capable of successfully defeating this detector. Furthermore meanwhile not adding a grainy noise to the image, our method successfully removes the JPEG blocking artifact. So it is expected that the proposed method can mislead the proposed detector in [13].

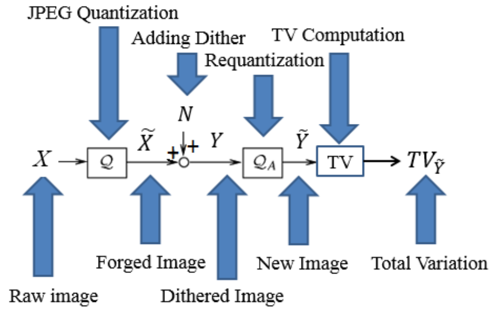


Fig. 1. Re-quantization with different Q_A to compute TVs

Authors in [7] have developed Stamm et al. [16] algorithm with a better perceptual quality and improved undetectability. Their framework has been based on a four steps JPEG artifact removal: total variation based deblocking in the spatial domain, perceptual DCT histogram smoothing, repetition of the first step and finally de-calibration operation. As can be seen from section III, it seems that the proposed method in this paper produces much better results.

The rest of this paper is organized as follows. In section II, our novel method for disguising the JPEG compression footprints is proposed. Section III illustrates experimental results and shows the effectiveness of the proposed algorithm. Moreover, comparison to other anti-forensic methods is discussed. The paper is concluded in section IV.

II. SR Based Artifact Concealing of JPEG Compression

Sparse representation (SR) based image denoising have been introduced by Elad and Aharon in [29]. The proposed method was based on representing an image by a linear combination of the least possible number of atoms. In that paper, first, a dictionary has been learned using the patches extracted from the input image. Then every patch of the image is represented by the linear combination of this dictionary atoms. The representation is sparse in the sense that the atom selection vector, is a sparse vector and most of its elements are zero.

In this paper we use the same technique to eliminate JPEG compression artifacts. First the compressed input image is divided into some $b \times b$ maximally overlapped patches. For an input image of size $M \times N$, there will be T=$(M-b+1) \times (N-b+1)$ patches of size $b \times b$. Then every patch matrix is reordered as a column of a $b^2 \times T$ matrix

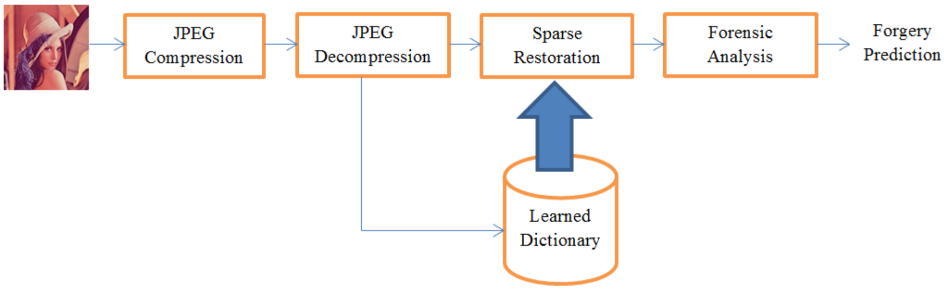
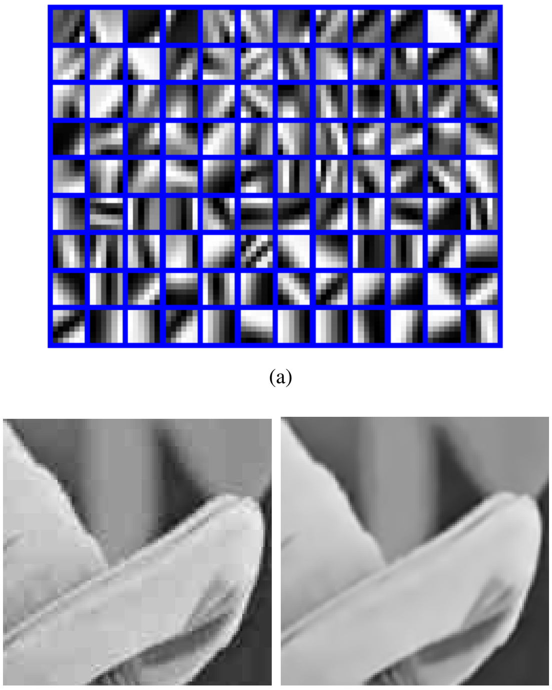


Fig. 2. The block diagram of the proposed method



(a)

(b)

(c)

Fig. 4. (a) The learned dictionary from Fig. 3b, using K-SVD; (b) The zoomed part of JPEG compressed image; (c) The zoomed part of the restored image

called Y. Then a redundant dictionary D is learned over this data set, using the K-SVD algorithm [30]. Then the patches are restored using OMP and the whole image is constructed by replacing every patch with its representations average.

Fig. 3 shows a practical example of performing this technique. The corresponding learned dictionary is shown in Fig. 4a. Note that to get better results, for every input image, we learn an adapted dictionary. Inspecting Fig. 3, shows that the introduced method can easily disguise most of the DCT based forensic traces. Our experiments show that modern forensic algorithms can not detect the traces of compression. In addition, comparing Fig. 4b and Fig. 4c shows that using the proposed method, the JPEG blocking artifact is properly canceled so it can be expected that the forensic methods based on blocking distortion like [13] can easily be defeated.

In order to perform the proposed noise reduction algorithm on f, which is a rewritten $M \times N$ matrix as an $C \times 1$ vector ($C = M \times N$), the K-SVD algorithm is used. We should learn the dictionary $D \in \mathbb{R}^{b^2 \times S}$ with respect to the following cost function minimization scheme to recover the image as u. S is the dictionary size and usually is selected so that $S \gg b^2$ to satisfy the redundancy condition.

$$\min_{\{\gamma_{i,j}\},D,u} \lambda \|f-u\|^2 + \frac{1}{2}\sum_{(i,j)\in P}\left(\|D\gamma_{i,j} - R_{i,j}u\|^2 + \mu_{i,j}\|\gamma_{i,j}\|_0\right) \quad (1)$$

The first term is the data fitting term. Where u is the denoised image (a vector of the same size of f), λ is a positive wight for the data fitting term and $\|.\|^2$ is the Euclidean norm of a vector. Minimizing this term, will result in a similar u and f.

The second term is used to make a proper redundant dictionary to represent each patch of the form $R_{i,j}u$ as a sparse linear combination of the form $D\gamma_{i,j}$. Where $R_{i,j}$ is a binary mask matrix of size $b^2 \times C$ used to extract patches from u and $\gamma_{i,j}$ is a $S \times 1$ vector, containing the weights of the contributing dictionary atoms in $R_{i,j}u$ representation. The sparsity condition is achieved by the last part of this term i.e. $\mu_{i,j}\|\gamma_{i,j}\|_0$, where $\|.\|_0$ indicates the number of non-zero elements of a vector and guarantees the sparsity condition and $\mu_{i,j}$ is a positive weight specified for each patch. Moreover, P is a set denoting the indexes of patches.

$$P = \{1,2,3,...,M-b+1\} \times \{1,2,3,...,N-b+1\}$$

To recover u in equation (1) a two steps iterative algorithm is performed multiple times. In the first step, we use an initial dictionary D and assume $f = u$, and then compute $\gamma_{i,j}$ per patch using orthogonal matching pursuit (OMP).

$$\gamma_{i,j} = \min_{\gamma}(\|D\gamma - R_{i,j}u\|^2 + \mu_{i,j}\|\gamma\|_0) \quad (2)$$

In the second step, we assume that we know u and $\gamma_{i,j}$ from (2) and we use K-singular value decomposition (K-SVD) algorithm to calculate the dictionary D so as (3) is minimized.

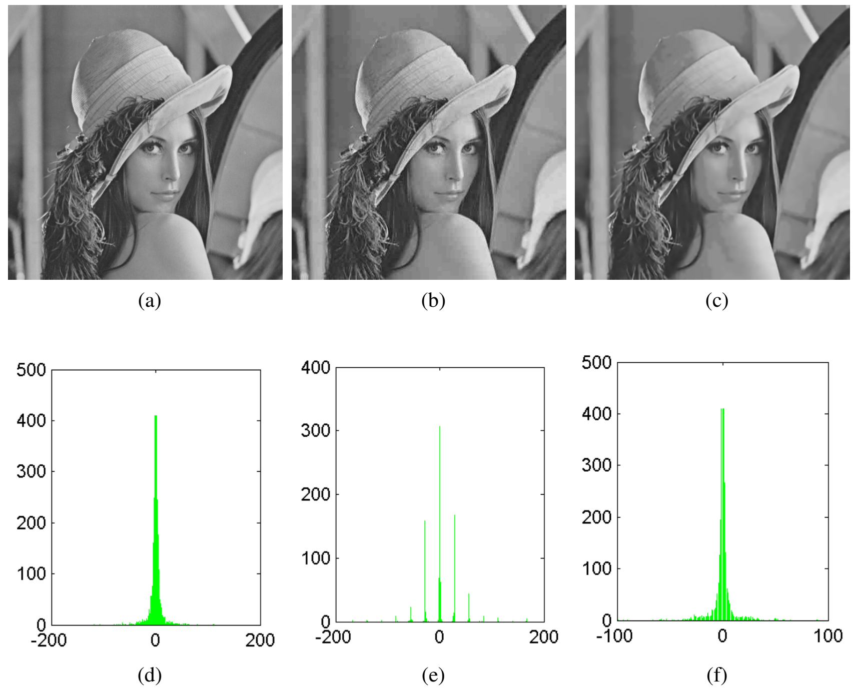


Fig. 3. (a) Uncompressed Lena image; (b) JPEG decompressed Lena image $Q = \%20$; (c) JPEG decompressed $Q = \%20$ and restored Lena image; (d), (e) and (f) DCT histograms of the above row

$$\min_{\gamma} \sum_{(i,j)\in P} (\|D\gamma - R_{i,j}u\|^2) \tag{3}$$

These steps are performed consecutively for multiple iterations. Afterward, knowing D and $\gamma_{i,j}$ we can compute u by averaging all the restored overlapping patches corresponding to a given patch and putting all these patches together to construct u. Averaging is performed according to the weight of each patch.

It can be expected that this averaging will reduce the JPEG compression distortion. Furthermore, it is shown that this procedure successfully eliminates forensic footprints of the JPEG compression history and is capable of defeating the state-of-the-art forensic algorithms like [11].

III. Experiments and Results

The proposed algorithm is applied to the UCID-v2 color image database [31] and is tested extensively according to the block diagram shown in Fig. 2. The UCID-v2 image dataset consists of 1338 uncompressed color images of different objects. All images in this database have a resolution of 512×384. By discarding chroma channel, each picture is first converted to a gray-scale image. Then %50 of them are chosen randomly. All the images in this selection, are JPEG compressed.

We have conducted two experiments. In the first experiment, the quality factors are uniformly sampled in the set $Q = \{30, 40, 50, 60, 70, 80, 90, 95\}$. In the second experiment, for every $q \in Q$ we conduct a separate test and all the compressions are performed using a single q.

In every experiment, the compressed images pass through the proposed method for concealing the traces of JPEG compression i.e. every input image is divided into 6×6 pixels of maximally overlapped blocks. Using these patch set, an overcomplete dictionary is trained using the K-SVD algorithm. So each atom in this dictionary has 36 elements. The size of the dictionary is chosen to be 3 times its atoms size i.e. 36×108. Using the K-SVD and the orthogonal matching pursuit algorithms consecutively in 10 iterations, and finally averaging the results, yields the restored images.

Afterward, the forensic analysis is performed according to [11]. This forensic analysis tries to distinguish never-compressed images from these compressed and restored images. Our experiments shows that the proposed method in this paper can successfully fool the forensic tools introduced in [11].

The results of the first experiment is shown in Fig. 5. This figure shows two ROC curves in one diagram for the proposed detector in [11]. One of the ROC curves is the result of detecting anti-forensically dithered images as in [16] and the other is the result of the same detector for the anti-forensically doctored images using the proposed method in this paper. The closer the curve to the bisector line, the better forensic detector is fooled. From Fig. 5, it is obvious that our proposed method can make the forensic detector in [11] to produce nearly random guess results.

The results of the second experiment is shown in Fig. 6.

TABLE I
JPEG FORENSIC DETECTORS IN FIG. 7 [7]

K_F	the JPEG blocking artifact detector [4];
K_{Luo}	the JPEG identifying detector [14];
K_{Luo}^Q	the quantization step estimation based detector in [14];
K_V	the TV-based JPEG forensic detector [11];
K_L	the calibration based detector [15];
K_U^1,K_U^2	the JPEG blocking artifact detector [17];

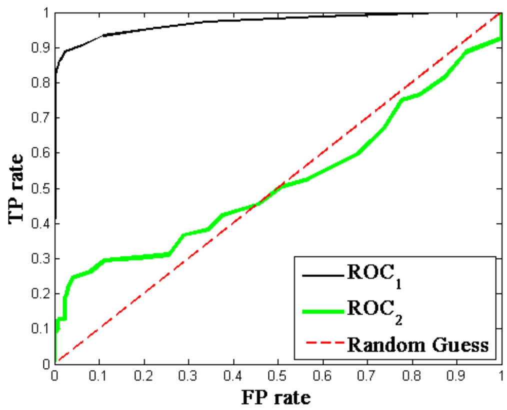


Fig. 5. Comparison of ROC curves of the detector in [11] ROC_1: The ROC result for the anti-forensic method in [16]; ROC_2: The ROC result for the proposed anti-forensic method

This figure shows the effectiveness of the proposed method for different quality factors (compression ratios). The equal error rate parameter, is an indicator of the detector effectiveness. The lower the equal error rate value, the higher the accuracy of the forensic classifier. From Fig. 6, it can be seen that except for very high compression ratios, our proposed method can significantly reduce the accuracy of the detector, insofar as makes it produce nearly random guess predictions. However the results for the very high quality factors are acceptable.

As another comparison to other works, authors in [7] have proposed a JPEG anti-forensic method to hide the traces of JPEG compression. As in Fig. 7, and Fig. 5, our work can be compared to that paper. From Fig. 7, it seems that the proposed forensic detector in [11], is one of the toughest detectors to defeat(see the K_V curve). By comparing the K_V curve in Fig. 7, and ROC_2 curve of Fig. 5, it can be easily seen that our proposed method is performing much better than the proposed anti-forensic algorithm in [7]. To make it easier to compare these results, the ROC_2 curve has been superimposed to the results in Fig. 7. Other curves in Fig. 7 show the results of applying anti-forensic method in [7] on different types of forensic detectors. Table I lists these detectors which have already been introduced in section I-B.

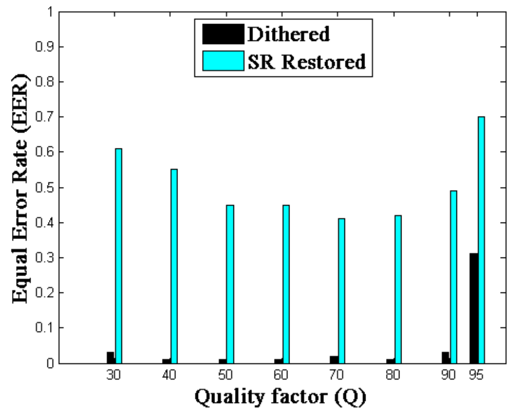


Fig. 6. Comparison of Equal Error Rate (EER) values of the detector in [11] for different quality factors. Dark Bars: The EER results for the anti-forensic method in [16]; Light Bars: The EER results for the proposed anti-forensic method

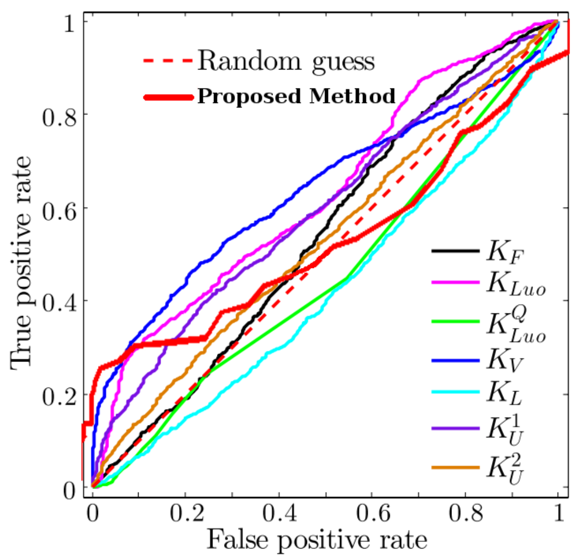


Fig. 7. The result of anti-forensic method in [7] on different types of forensic detectors as well as our proposed anti-forensic method superimposed from Fig. 5. K_V is the result of applying the anti-forensic algorithm in [7], and forensic analysis using the proposed detector in [11]. This curve (as the worst result in [7]) can be compared with our proposed method. For more details, one can refer to [7].

IV. CONCLUSION

In this paper we proposed a novel method for concealing the traces of JPEG compression. The proposed method can successfully fool the state-of-the-art forensic methods. Moreover, it has the advantage of noise reduction for a better perceptual performance. As an improvement to the proposed approach, one can think of adding more stages to the noise cancellation mechanism e.g. use of total variation minimization methods as shown in [32]. Due to the computational costs of the training an over-complete dictionary for each image, we can search for a more efficient approach. As an effort to increase the performance, one can try to train a global dictionary over a large uncompressed image database and use it for the sparse representation and the subsequent image anti-forensics.

As a part of cat-and-mouse game of forensic analysis, now we are working on a forensic method, capable of revealing the traces of this anti-forensic method. Anyway, this work can help forensic analysts to better know pitfalls and improve their algorithms.

References

[1] J. Fridrich, "Digital image forensics," *IEEE Signal Processing Magazine*, vol. 26, no. 2, pp. 26–37, mar 2009.

[2] C. Podilchuk and E. Delp, "Digital watermarking: algorithms and applications," *IEEE Signal Processing Magazine*, vol. 18, no. 4, pp. 33–46, jul 2001.

[3] H. Farid, "Digital Image Ballistics from JPEG Quantization," Dept. of Computer Science, Dartmouth College, Tech. Rep., 2006.

[4] Zhigang Fan and R. de Queiroz, "Identification of bitmap compression history: jpeg detection and quantizer estimation," *IEEE Transactions on Image Processing*, vol. 12, no. 2, pp. 230–235, feb 2003.

[5] H. Huang, W. Guo, and Y. Zhang, "Detection of Copy-Move Forgery in Digital Images Using SIFT Algorithm," in *2008 IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application*, vol. 3. IEEE, dec 2008, pp. 272–276.

[6] T. Bianchi and A. Piva, "Detection of nonaligned double JPEG compression based on integer periodicity maps," *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 2, pp. 842–848, apr 2012.

[7] W. Fan, K. Wang, F. Cayre, and Z. Xiong, "JPEG Anti-Forensics With Improved Tradeoff Between Forensic Undetectability and Image Quality," *IEEE Transactions on Information Forensics and Security*, vol. 9, no. 8, pp. 1211–1226, aug 2014.

[8] T. Bianchi and A. Piva, "Image Forgery Localization via Block-Grained Analysis of JPEG Artifacts," *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 3, pp. 1003–1017, jun 2012.

[9] H. Farid, "Digital image ballistics from JPEG quantization: A followup study," *Department of Computer Science, Dartmouth College, Tech. Rep. TR2008-638*, vol. 7, pp. 1–28, 2008.

[10] J. D. Kornblum, "Using JPEG quantization tables to identify imagery processed by software," *Digital Investigation*, vol. 5, pp. S21–S25, sep 2008.

[11] G. Valenzise, M. Tagliasacchi, and S. Tubaro, "Revealing the Traces of JPEG Compression Anti-Forensics," *IEEE Transactions on Information Forensics and Security*, vol. 8, no. 2, pp. 335–349, feb 2013.

[12] Zhigang Fan and Fu Li, "Reducing artifacts in JPEG decompression by segmentation and smoothing," in *Proceedings of 3rd IEEE International Conference on Image Processing*, vol. 1. IEEE, 1996, pp. 17–20.

[13] S. Ye, Q. Sun, and E.-C. Chang, "Detecting Digital Image Forgeries by Measuring Inconsistencies of Blocking Artifact," in *Multimedia and Expo, 2007 IEEE International Conference on*, vol. 117543, no. 2. IEEE, jul 2007, pp. 12–15.

[14] W. Luo, J. Huang, and G. Qiu, "JPEG Error Analysis and Its Applications to Digital Image Forensics," *IEEE Transactions on Information Forensics and Security*, vol. 5, no. 3, pp. 480–491, sep 2010.

[15] S. Lai and R. Böhme, "Countering counter-forensics: the case of jpeg compression," in *Information hiding*. Springer, 2011, pp. 285–298.

[16] M. C. Stamm and K. J. R. Liu, "Anti-forensics of digital image compression," *IEEE Transactions on Information Forensics and Security*, vol. 6, no. 3, pp. 1050–1065, sep 2011.

[17] W. Fan, K. Wang, F. Cayre, and Z. Xiong, "A variational approach to JPEG anti-forensics," in *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, no. 2. IEEE, may 2013, pp. 3058–3062.

[18] H. Li, W. Luo, and J. Huang, "Countering anti-JPEG compression forensics," in *Proceedings - International Conference on Image Processing, ICIP*, no. 61003243, 2012, pp. 241–244.

[19] T. Pevny, P. Bas, and J. Fridrich, "Steganalysis by subtractive pixel adjacency matrix," *IEEE Transactions on Information Forensics and Security*, vol. 5, no. 2, pp. 215–224, June 2010.

[20] A. C. Popescu and H. Farid, "Statistical Tools for Digital Forensics," in *in 6Th International Workshop on Information Hiding*, 2004, vol. 3200, pp. 128–147.

[21] F. Huang, J. Huang, and Y. Q. Shi, "Detecting Double JPEG Compression With the Same Quantization Matrix," *IEEE Transactions on Information Forensics and Security*, vol. 5, no. 4, pp. 848–856, dec 2010.

[22] J. He, Z. Lin, L. Wang, and X. Tang, "Detecting Doctored JPEG Images Via DCT Coefficient Analysis," in *European Conference. Computer Vision*, Graz, Austria, 2006, pp. 423–435.

[23] W. Luo, Z. Qu, J. Huang, and G. Qiu, "A Novel Method for Detecting Cropped and Recompressed Image Block," in *2007 IEEE International Conference on Acoustics, Speech and Signal Processing - ICASSP '07*, vol. 2. IEEE, 2007, pp. II–217–II–220.

[24] N. Bayram, Sevinc and Sencar, Husrev Taha and Memon, "A survey of copy-move forgery detection techniques," in *IEEE Western New York Image Processing Workshop*, 2008, pp. 538–542.

[25] T. Bianchi, A. De Rosa, and A. Piva, "Improved DCT coefficient analysis for forgery localization in JPEG images," in *2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, may 2011, pp. 2444–2447.

[26] A. Taimori, F. Razzazi, A. Behrad, A. Ahmadi, and M. Babaie-Zadeh, "Quantization-Unaware Double JPEG Compression Detection," *Journal of Mathematical Imaging and Vision*, vol. 54, no. 3, pp. 269–286, mar 2016.

[27] J. Price and M. Rabbani, "Biased reconstruction for JPEG decoding," *IEEE Signal Processing Letters*, vol. 6, no. 12, pp. 297–299, dec 1999.

[28] L. I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D*, vol. 60, pp. 259–268, 1992.

[29] M. Elad and M. Aharon, "Image Denoising Via Sparse and Redundant Representations Over Learned Dictionaries," *IEEE Transactions on Image Processing*, vol. 15, no. 12, pp. 3736–3745, dec 2006.

[30] M. Aharon, M. Elad, and A. Bruckstein, "K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation," *IEEE Transactions on Signal Processing*, vol. 54, no. 11, pp. 4311–4322, nov 2006.

[31] G. Schaefer and M. Stich, "UCID - An Uncompressed Colour Image Database," in *SPIE, Storage and Retrieval Methods and Applications for Multimedia*, M. M. Yeung, R. W. Lienhart, and C.-S. Li, Eds., vol. 5307, dec 2003, pp. 472–480.

[32] H. Chang, M. K. Ng, and T. Zeng, "Reducing Artifacts in JPEG Decompression Via a Learned Dictionary," *IEEE Transactions on Signal Processing*, vol. 62, no. 3, pp. 718–728, feb 2014.