ADDING GAUSSIAN NOISE TO "DENOISE" JPEG FOR DETECTING IMAGE RESIZING

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ABSTRACT

In this paper, we propose robust methods to detect image resizing. A common problem affecting most resizing detection algorithms is that they are susceptible to JPEG compression attacks. The reason is that JPEG compression introduces its own periodicity, as it works on 8×8 blocks. In our proposed approach, we add a suitable amount of Gaussian noise to a resized and JPEG compressed image so that the periodicity due to JPEG compression is suppressed while that due to the resizing is retained. The controlled Gaussian noise addition works better than median filtering and weighted averaging based filtering for suppressing the JPEG induced periodicity.

Index Terms— image forensics, image resizing, bilinear interpolation, Gaussian noise addition, JPEG compression,

1. INTRODUCTION

Digital image forensics is a new emerging field. The aim of image forensics is to detect whether an image has been tampered with. With the widespread usage of high-resolution digital cameras and highly advanced photo editing software, image tampering has become more commonplace. Why is resizing or rotation often present in artificially created images? When a doctored photograph is created by digitally compositing individual images, it may be often required to re-sample (resize/rotate/stretch) the image to make it look natural.

In [1], Popescu et al discuss how re-sampling introduces statistical correlations and describe methods to automatically detect them based on the Expectation-Maximization (EM) algorithm [2]. The specific form of the correlations indicates the exact form of the re-sampling. However, the EM-based method is very susceptible to JPEG attacks, especially when the JPEG quality factor (QF) is 97 or lower [1]. The reason is that the periodic JPEG blocking artifacts coincide with the periodic patterns introduced by re-sampling.

For images that have been resized using bilinear/bicubic interpolation, Gallagher [3, 4] has proposed techniques based on the variance of the second difference of interpolated images. This method is more robust than the correlation based method [1], though it applies only to up-sampled images. For JPEG images, the second difference based method works for a QF higher than 80 (observed later in Fig. 3).

In forensics, we can perform suitable post-processing on the image without worrying about its visual quality, as the processed image is just meant for forensic analysis. Though suppression of JPEG blockiness has been well studied [5, 6] to improve the image quality, such methods have not been incorporated in forensic applications. We propose a new approach to suppress JPEG artifacts by adding Gaussian noise for robust detection of image resizing. For the correlation detection method [1], we add controlled amounts of Gaussian noise to the resized and JPEG compressed image. By adjusting the noise level, the JPEG induced frequency components are suppressed while the correlation induced peaks are retained. Hence, the method works even after JPEG compression. The second difference method [3, 4] also works after JPEG compression with controlled Gaussian noise addition (Table 1). In this paper, JPEG "denoising" refers to suppressing the periodic artifacts introduced by JPEG while retaining the re-sampling induced periodicity. We compare our method to median, averaging and weighted averaging based filters for suppressing JPEG induced peaks.

2. JPEG "DENOISING" THROUGH GAUSSIAN NOISE ADDITION

We show a synthetic example to demonstrate that adding Gaussian noise suppresses many frequencies introduced by JPEG compression (as shown in Fig. 1). Here, P_i and F_i refer to an image in pixel domain and its corresponding Discrete Fourier Transform (DFT) magnitude domain representation, respectively ($1 \leq i \leq 4$). We have used a 512×512 DFT.

We take an image P_1 of constant intensity and hence, F_1 has only one non-zero component (DC). We insert 4 peaks in F_1 (Fig. 2(a)) at $A_1 = (f_1, g_1)$, $A_2 = (f_2, g_2)$, $A_3 = (f_3, g_3)$, and $A_4 = (f_4, g_4)$, while maintaining conjugate symmetry, to obtain F_2 and hence P_2. In our example, we have A_1 as $(117, 117)$, A_2 as $(-37, 37)$, A_3 as $(-117, -117)$, and A_4 as $(37, -37)$. After JPEG compressing P_2 at a QF of 75, we obtain P_3 and hence F_3 (Fig. 2(b)) which has many frequency components, due to JPEG. There are two dominant orienta-

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tions in F_3 (Fig. 2(b)) - one along (parallel to) the line joining A_1 and A_3 and the other along (parallel to) the line joining A_2 and A_4. Starting from the center and going to a corner point ($(-256, 256)$ or $(256, -256)$), there are 8 parallel lines (including the corner point) - this shows that JPEG, by acting on 8×8 blocks, introduces a periodicity of 8 in the image.

We add Gaussian noise to P_3 (*the Gaussian noise addition always occurs in the pixel domain*), at a Signal-to-Noise Ratio (SNR) of 10 and -5 dB, to obtain P_4 and the resultant F_4 plots are shown in Fig. 2(c) and Fig. 2(d), respectively. In Fig. 2(d), we observe 4 dominant frequency terms, at B_1, B_2, B_3 and B_4, from which we can compute $\{A_i\}_{i=1}^4$. The locations of these new peaks ($\{B_i\}_{i=1}^4$) are given by: $(f_i + f_j, g_i + g_j)$, $1 \le i, j \le 4$, $i \ne j$. The locations of $\{B_i\}_{i=1}^4$ are: $B_1 = (80, 154)$, $B_2 = (-154, -80)$, $B_3 = (-80, -154)$ and $B_4 = (154, 80)$. E.g. $B_1 = A_1 + A_2$.

We replace the Gaussian noise addition by (3×3 window based) median filtering (Fig. 2(e)), (3×3 window based) mean filtering (Fig. 2(f)), and 3×3 (Fig. 2(g)) and 5×5 (Fig. 2(h)) weighted average filters. The convolution kernels in the pixel domain for these filters are $[1\ 1\ 1;\ 1\ \boxed{8}\ 1;\ 1\ 1\ 1]/16$ and $[1\ 1\ 2\ 1\ 1;\ 1\ 2\ 4\ 2\ 1;\ 2\ 4\ \boxed{16}\ 4\ 2;\ 1\ 2\ 4\ 2\ 1;\ 1\ 1\ 2\ 1\ 1]/60$, respectively (the boxed value represents the origin). It is seen that adding Gaussian noise (at a suitable SNR) is most successful in suppressing the JPEG induced frequencies.

In general, images may have a wide range of frequency values, making it more difficult to observe the effects of JPEG compression from the DFT magnitude plots. E.g. if we start with a natural image P_1 in Fig. 1 and perform the remaining steps, the peaks $\{B_1, \cdots, B_4\}$ will be very distinct only when the DFT magnitudes at $\{A_1, \cdots, A_4\}$ are much higher than the other frequency components.

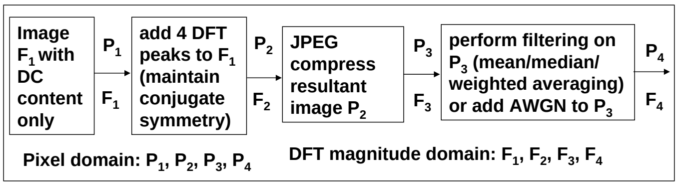


Fig. 1. The block diagram for the synthetic example

3. DETECTING RESIZING AFTER JPEG ATTACKS

In [3], it has been shown that the variance of the second difference of the interpolated signal has the same periodicity as the sampling rate of the original signal. Here, the second derivative was computed along each row of the image and then averaged over all rows to obtain a trace. The DFT of the trace is then examined for peaks. Considering the DFT plot on a normalized frequency grid, the peaks are observed at integer multiples of $1/\hat{f}$, when the periodicity equals $\hat{f}$, for bilinear interpolation. Here, we have considered the performance of this second difference method for varying levels of JPEG compression. For all the results shown for this method (Fig. 3-7), the results have been averaged across 50 images.

3.1. Effects of JPEG compression

In Fig. 3, we resize the image by a factor of 3 using bilinear interpolation, followed by JPEG compression. As explained in Sec. 2, JPEG introduces periodicity by a factor of 8. In Fig. 3, $\{J_1, \cdots, J_6\}$ denote the six JPEG peaks, where two consecutive peaks are 1/8 apart from each other (except J_3 and J_4, which are symmetric w.r.t. the center point) in the normalized frequency domain. We normalize the DFT spectrum without considering the high magnitude DC peaks.

$\{S_1, S_2\}$ denote the sampling peaks which are dominant over the JPEG peaks at high QF. To find the resize factor, we need to obtain the exact locations of the sampling peaks. One approach can be to zero out the JPEG peaks (since their locations are known). However, when the resize factor is a multiple of 4, some sampling peaks will coincide with some JPEG induced peaks. Hence, we suggest methods to suppress the JPEG peaks while retaining the sampling peaks.

On progressively lowering the QF (more severe compression), the JPEG peaks increase in magnitude. Closer to a QF of 70-80, the peaks due to re-sampling and JPEG compression are almost of the same magnitude. For lower QF, the JPEG peaks dominate over the sampling peaks and hence, the DFT magnitude plots reveal only a periodicity of 8, due to JPEG.

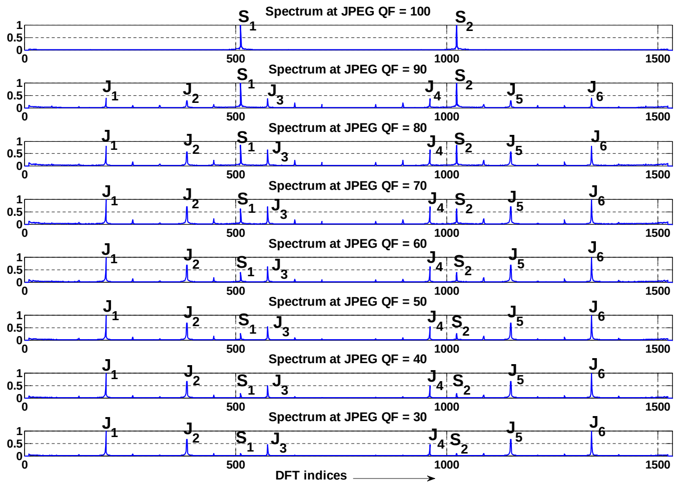
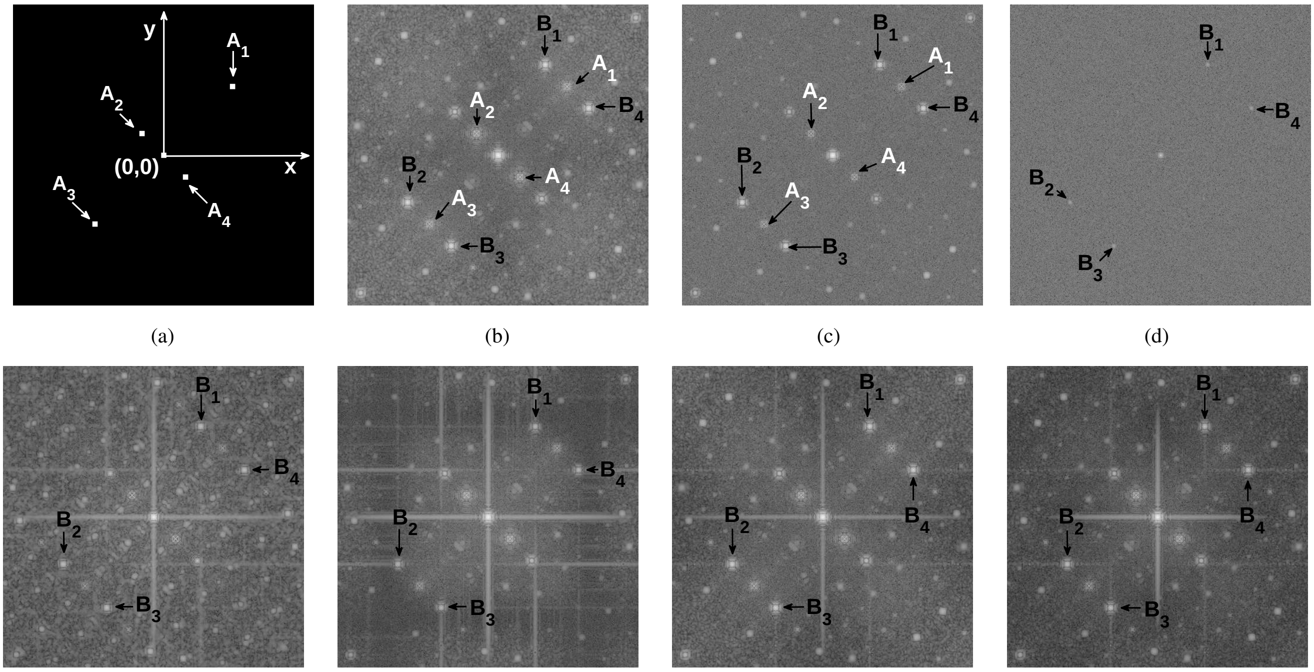


Fig. 3. JPEG compression performed (after bilinear interpolation by a factor of 3) at different QF, from 30-100

3.2. Masking JPEG Peaks using AWGN

Based on the observation in Sec. 2, we add AWGN (Additive White Gaussian Noise) to a resized (by 3) and then JPEG compressed image. We find that with increasing noise levels (Fig. 4), the magnitude of the JPEG peaks is more significantly reduced than that of the sampling peaks. Thus, AWGN suppresses the JPEG induced periodicity. At a SNR of 20 dB, the JPEG peaks are masked but the sampling peaks are still



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 2. F_2 is shown in (a), F_3 is shown in (b), F_4 is shown from (c)-(h) for the following post-processing steps (10 dB SNR AWGN addition, -5 dB SNR AWGN addition, median filtering, mean filtering, 3×3 and 5×5 windowed weighted averaging).

visible. However, excessive noise addition also suppresses the sampling peaks, as observed for 15 dB SNR.

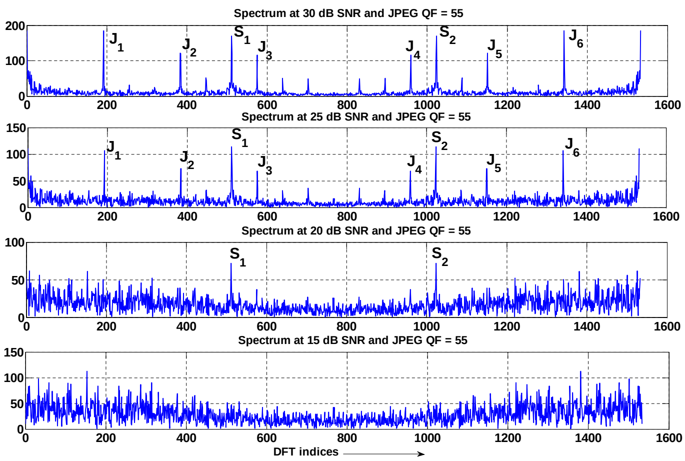


Fig. 4. By adding suitable amount of Gaussian noise, the peaks due to JPEG compression are suppressed while still retaining the sampling peaks - as seen at 20 dB SNR. Below 20 dB SNR, both the JPEG and sampling peaks are suppressed.

One can vary the SNR level of the AWGN to be added based on the QF of the resized JPEG image and the noise level should be high enough to mask the JPEG peaks, while retaining the sampling peaks. We find suitable SNR ranges for the added AWGN for a host of JPEG compression factors ($40 \leq QF \leq 80$) as shown in Table 1.

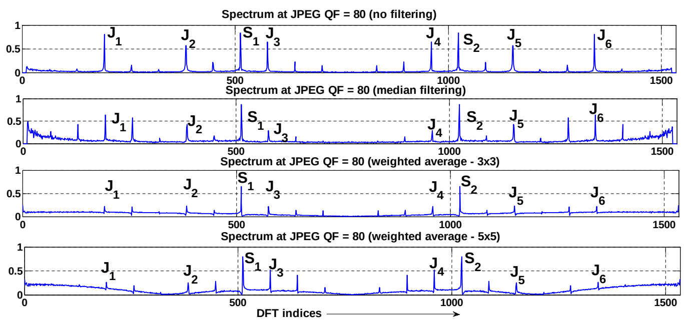


Fig. 5. Filtering the JPEG compressed image, at QF of 80

Table 1. Strength of AWGN to add for a given JPEG QF

JPEG QF	SNR Range (dB)	JPEG QF	SNR Range (dB)
80	[20-50]	75	[20-50]
70	[20-40]	65	[20-30]
60	[20-30]	55	[20-25]
50	20	40	20

We consider other filters (median filter, 3×3 and 5×5 weighted average filter, which are described in Sec. 2) to "denoise" JPEG images, for different JPEG QF (Fig. 5-7). In Fig. 5, we observe that the sampling peaks can be better distinguished for the 3×3 and 5×5 weighted average filters. In Fig. 6, S_1 and S_2 can be much better distinguished using 3×3 than 5×5 filter. In Fig. 7, for 3×3 filter, S_1 and S_2 are almost equal to J_1 and J_6, in magnitude. However, adding AWGN "denoises" JPEG better than all these filters.

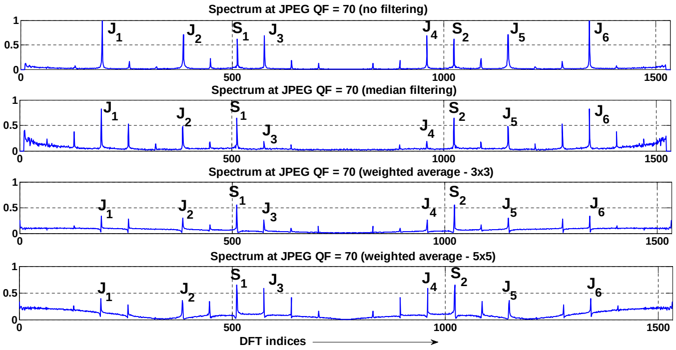


Fig. 6. Filtering the JPEG compressed image, at QF of 70

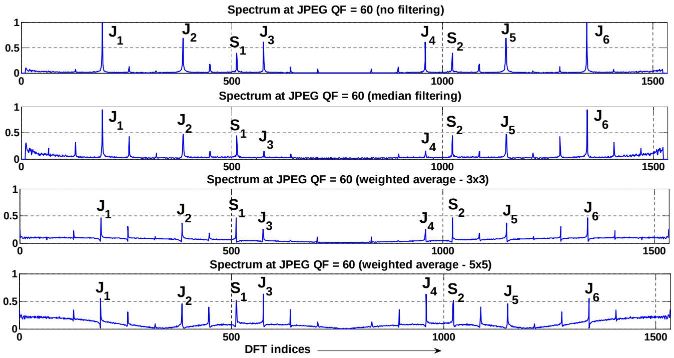


Fig. 7. Filtering the JPEG compressed image, at QF of 60

4. EFFECT ON THE EM-BASED METHOD

In Popescu et al's EM-based algorithm [1], each re-sampled pixel is assumed to be a linear combination of its neighbors. Each pixel's probability of being a linear combination of its neighbors is then estimated using the EM-based learned weights. This matrix of probability values, called the "p-map", exhibits a periodic pattern. Hence, peaks are seen in the DFT plot of the p-map only for re-sampled images, making the peaks an indicator of re-sampling. To estimate the probability, a 3×3 window was used across the entire image. In our case, we use a 1×5 window across a row and repeat the same for all rows. In Fig. 8, we see that the 3 peaks clearly visible in (a) get smeared due to JPEG (b). By adding AWGN, we are able to retrieve the periodicity as shown in (c) and (d).

5. CONCLUSIONS

Various resizing detection algorithms fail after JPEG compression since it introduces significant peaks in the frequency domain that interfere with the periodicity introduced by resizing. We have shown that adding Gaussian noise is as an effective "denoising" technique to mask the effects of JPEG. By varying the strength of the Gaussian noise based on the JPEG quality factor, we can suppress the JPEG peaks while still retaining the sampling peaks. Though we have focussed solely on image resizing detection, the proposed "JPEG induced peak suppression" can be applied to other methods which fail due to JPEG attacks and where the visual quality

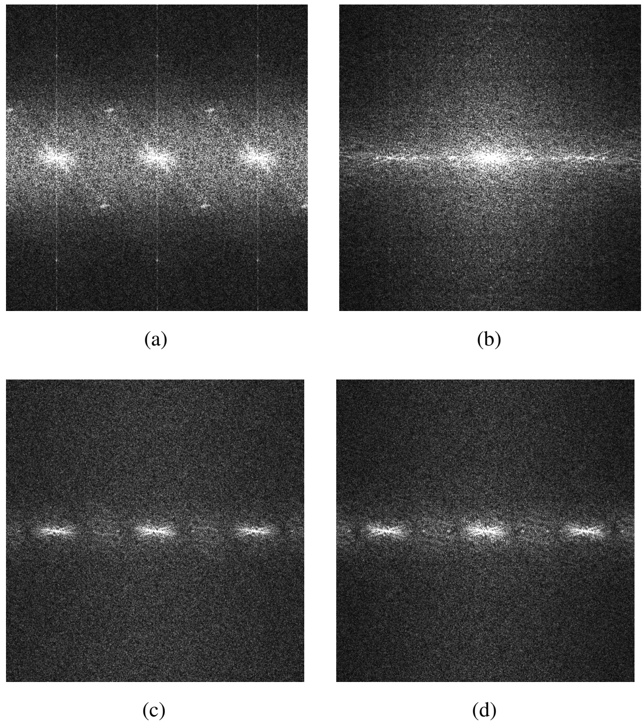


Fig. 8. DFT of the p-map after (a) resizing the image by a factor of 3 (b) JPEG on the resized image at a QF of 85 (c) adding AWGN on JPEG image at 35 dB SNR, (d) 40 dB SNR

of the final image is not of interest. In future, we shall further explore why the noise addition masks the JPEG blockiness much better than traditional filters.

References

[1] A. C. Popescu and H. Farid, "Exposing digital forgeries by detecting traces of re-sampling," *IEEE Transactions on Signal Processing*, vol. 53, no. 2, pp. 758–767, 2005.

[2] A. Dempster, N. Laird, and D. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *Journal of the Royal Statistical Society, Series B*, vol. 99, no. 1, pp. 1–38, 1977.

[3] A.C. Gallagher, "Detection of linear and cubic interpolation in JPEG compressed images," in *Computer and Robot Vision, 2005. Proc. The 2nd Canadian Conference on*, May 2005, pp. 65–72.

[4] A.C. Gallagher, "Method for detecting for image interpolation," in *US Patent No. US 7,251,378, B2*, October 2004.

[5] A. Nosratinia, "Denoising of JPEG images by re-application of JPEG," *Journal of VLSI Signal Processing*, vol. 27, pp. 69–79, 2001.

[6] Y.L. Lee, H.C. Kim, and H.W. Park, "Blocking effect reduction of JPEG images by signal adaptive filtering," *Image Processing, IEEE Tran. on*, vol. 7, no. 2, pp. 229–234, Feb 1998.