Resampling Detection in Digital Images: A Survey

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ABSTRACT

Usually digital image forgeries are created by copy-pasting a portion of an image onto some other image. Forged area is often resized & rotated to make it proportional with respect to neighboring unforged area. This is called as resampling operation which changes certain characteristics of the pasted portion. Thus resampling is the default fingerprint present in most of the forged image and resampling detection became a standard tool in digital image forensics. Generally resampling artifacts are not visible to human eye in interpolated images but periodic correlations get introduced in image pixels because of it. These periodic interpolation artifacts present in pixel intensities or other format of data representation such as DFT, wavelet are the features which detectors look for in order to decide if an image, or a segment of image, has undergone a geometrical transformation. JPEG compression process creates its own correlation in image & may confuse resampling detectors. This paper addresses various resampling detection techniques in uncompressed image as well as re-compressed JPEG images.

General Terms

Image Forensic, Passive forgery detection

Keywords

Resampling, EM Algorithm, second order difference, variance, interpolation.

1. INTRODUCTION

Among available framework of passive forgery detection techniques 'Resampling Detection' has emerged as a very promising technique. In order to obtain convincing forgery, it is often necessary to apply a geometrical transformation to some portions of the manipulated images, requiring the application of a resampling step. Thus resampling effect will be available in almost all types of forgery. Resampling detectors try to extract features from a given possibly manipulated image or whole image (usually a central square area of size $N \times N$). Some of the existing methods use a parameter computed from the extracted features as a test function to be compared against a detection threshold in order to decide positive or negative resampling. Many techniques extract features from images & train classifier to identify possible resampling. Prasad[1] & Galhagar[2] used properties of second order derivative for resampling detection. These algorithms are usually assessed by analyzing supervised resized images (both down-scaled and up-scaled), that use some specific interpolation methods (i.e. bilinear, cubic or nearest-neighbour). M. Kirchner [3] proposed an efficient method by directly applying the converged resampling coefficients to detect the tampered regions. Mahdian et al [4] proposed their method to extract the periodical property of the resampled signals based on analyzing the periodic characteristic of the covariance of the second order derivatives.

1.1 Resampling Image

Figure 1[5] shows bilinear interpolation of 2-D image in which kernel window (b) is moved over spike image(c) created from the original image(a). Effective value is calculated at the centre of each kernel window which gives resampled image (d). On

the resultant image if we apply reverse kernel(e) we can see resultant periodicity in form alternate row & columns of zeros. Resampling detectors exploit these periodic artifacts, which are generally present in the derivatives of a resampled signal..

There exist many survey papers explaining various digital image forgery detection techniques such as [5][6][7] but most of them are bibliographic listing of approaches used for forgery detection. As this is a very vast area it is not possible to explain all the techniques in detail in one paper. In this paper we have concentrated only on fingerprint created by resampling & categorized resampling detection techniques based on assumed hypothesis for forgery. The remaining content of this paper is organized as follows. Section 2 & 3 explains various types of resampling detection techniques in uncompressed & compressed images respectively. Section 4 addresses major work on these techniques & their comparison.

2. RESAMPLING DETECTION TECHNIQUES

If we assume each row of image as 1 D array then from figure 1 we can see that q^{th} sample in the original sequence will be the $[q+(q-1)]^{\text{th}}$ sample in resampled sequence. Hence, the occurrence of zero is within fixed interval samples. Moreover, the position at which a zero occurs within the sample interval is precisely fixed by the resampling degree. Hence, in every interval of samples, the second difference produces zero in a periodic pattern which is not present in natural images & characterizes a resampled images.

2.1 Properties of Second difference

If 1-D sequence gets resampled with a factor $p/q \geq 2$, then every q samples in the original sequence will get expanded to p samples, with a few original samples retained in the resulting sequence. If original sequence had M samples, then total $(p*M)/q$ equally spaced samples will be present in resampled signal. If interpolation is linear or cubic the first difference of the pair of signals will be same & so second difference becomes zero. To detect resampling Prasad et al [1] constructed, a binary sequence $p[k]$ from the sequence of second differences $x''[k]$, as shown in equation (1).

$$p[k] = \begin{cases} 1 & \text{if } |x''[k]| = 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Generally resampled portion is smoothened to get it mixed with neighbouring area hence exact zero may not appear in second difference. In such case periodicity of zero crossing of second difference can be used. Zero-crossings of the second difference of a resampled sequence exhibits a periodicity that is absent in a non-resampled sequence. Linear Cubic & Gaussian smoothing kernels exhibits this property. A binary sequence can be constructed as per conditions in equation (2).

The DFT magnitude of this binary sequence displays distinct peaks[1], showing the presence of periodic zeros in the second difference.

$$p[k] = \begin{cases} 1 & \text{if } x''[k] > 0 \text{ and } x''[k+1] \leq 0 \\ 1 & \text{if } x''[k] < 0 \text{ and } x''[k+1] \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

To extend these techniques from 1D to 2D each row or column is treated as a 1-D sequence & resulting binary sequences are stacked together to form a binary image. The region which has undergone resampling, will be visible distinctly [1]. In [8], Gallagher proposed a simple algorithm to detect up-scaled images that were interpolated using linear or cubic interpolation. As in [1] he also showed that the variance of the second difference of the interpolated signal has the same periodicity as the sampling rate of the original signal. To detect interpolation, the second derivative of image of size (R,C) was computed along each row for $1 \leq i \leq C-1$ with the difference equation(3).

$$d_p(i, j) = 2p(i, j) - p(i, j+1) + p(i, j-1) \quad (3)$$

The signal $dp(i,j)$ is a two-dimensional signal made from the second derivative signals for each row of the image. They averaged together magnitudes of the row of second derivative signal to form pseudo-variance signal as shown in equation (4).

$$V_p(j) = \sum_{i=0}^R |d_p(i, j)| \quad (4)$$

They didn't found signature DFT in high resolution original cases of pseudo variance signal but found pronounced spike in the DFT of bilinear and bicubic interpolation cases.

2.2 Tamper detection using DCT high pass filtering

Whenever an image undergoes up-sampling, the spectra of the image gets periodically repeated. Low pass filter is used to retain only original spectra removing all the other copies of it. As all practical filters are non-ideal some high frequency remains in forged area. Prasad et al[1] identified this inconsistency of high frequency component by using careful high pass filtering. They computed block 8 by 8 DCT of the entire image & reconstructed image back retaining only few high frequency content. In their experiment reconstructed image marks out that pated pasted portion on original image.

A	B
C	D

a. Original image

1/4	1/2	1/4
1/2	1	1/2
1/4	1/2	1/4

b. Kernel image

A	0	B	0
0	0	0	0
C	0	D	0
0	0	0	0

c. Spike image

A	(A+B)/2	B	-
(A+C)/2	(A+B+C+D)/4	(B+D)/2	-
C	(C+D)/2	D	-
-	-	-	-

d. Resultant Resampled image

1/4	-1/2	1/4
-1/2	1	-1/2
1/4	-1/2	1/4

e. Reverse Kernel

-	0	-	0
0	0	0	0
-	0	-	0
0	0	0	0

f. Resultant periodicity

Fig. 1. Bilinear Interpolation[5]

2.3 Tamper detection using wavelets

Generally interpolation kernel smoothes the resampled portion in image because of which high frequency content of that portion becomes poor as compared to other non resampled portion of image. These low frequency component can be analyzed by using wavelet. Prasad et al [1] decomposed image into approximation (A) and three horizontal, vertical and diagonal (H,V and D) details & reconstructed image using only the

diagonal detail coefficients, D and discarding the others. In their work they marked resampled region with absence of high frequency component. Wavelet to be used to divide & reconstruct was selected heuristically .

2.4 Propescu & Farid's Method

If we know interpolation method then it is possible to find original signals & interpolated signals from resampled image. Propescu & Farid [9] suggested that type of correlations can be

determined if we are able to find neighborhood size N and the set of weights, $\vec{\alpha}$ that satisfy equation (5)

$$\vec{a}_i = \sum_{k=-N}^N \alpha_k \vec{a}_{i+k} \quad (5)$$

where $\vec{a}_i$ is the i^{th} row of the re-sampling matrix and $i = 3, 7, 11, \text{etc.}$ In another way if we know type of correlation $\vec{\alpha}$, then it is possible to find those samples which satisfy equation (6).

$$y_i = \sum_{k=-N}^N \alpha_k y_{i+k} \quad (6)$$

But in real resampled signals none of the information is available neither the re-sampling amount nor the specific forms of the correlations. Propescu & Farid[9] used expectation/maximization algorithm (EM) [7] to find samples which are correlated with neighborhood & type of correlations they have. They explained their algorithm for 1D signal which can be extended to 2D signal. They categorized each signal into one of the tow models. Samples which are correlated with neighbors belong to model M1 & non correlated samples belong to model M2. The EM algorithm iteratively executes E-estimation & M-maximization step. Probability of each signal belonging to model M1 & M2 is estimated in E step & type of correlation is calculated in M step. In the E-step, the probability of each sample y_i belonging to model M1 was obtained using Bayes' rule, equation (7).

$$\begin{aligned} \text{Prob}(y_{i,j} \in M_1 | y_{i,j}) \\ = \frac{\text{Prob}(y_{i,j} | y_{i,j} \in M_1) \text{Prob}(y_{i,j} \in M_1)}{\sum_{k=1}^2 \text{Prob}(y_{i,j} | y_{i,j} \in M_k) \text{Prob}(y_{i,j} \in M_k)} \end{aligned} \quad (7)$$

Where

$$\begin{aligned} \text{Prob}\{y_{i,j} | y_{i,j} \in M_1\} \\ = \frac{1}{\sigma\sqrt{2\pi}} \exp \left[-\frac{(y_{i,j} - \sum_{k=-N}^N \alpha_k y_{i+k,j+k})^2}{2\sigma^2} \right] \end{aligned} \quad (8)$$

and that $\text{Prob}\{y_{i,j} | y_{i,j} \in M_2\}$ is distributed over the range of possible values of the signal $\vec{y}$ uniformly. The variance σ of the Gaussian distribution equation (8) is estimated in the M-step. In first iteration of E-step $\vec{\alpha}$ is selected randomly & in the M-step, a new estimate of $\vec{\alpha}$ is computed using weighted least-squares, that is, minimizing the following quadratic error function in equation (9).

$$E(\vec{\alpha}) = \sum w(i) \left(y_i - \sum_{k=-N}^N \alpha_k y_{i+k} \right)^2 \quad (9)$$

Where the weights $w(i) = \text{Prob}(y_i \in M_1 | y_i)$ and $\alpha_0 = 0$. Error function in equation(9) is minimized by computing the gradient with respect to $\vec{\alpha}$ and after equating the result with zero which solves $\vec{\alpha}$ yielding equation (10).

$$\vec{\alpha} = (Y^T W Y)^{-1} Y^T W \vec{y} \quad (10)$$

where the matrix Y is

$$Y = \begin{bmatrix} y_1 & \cdots & y_N & y_{N+2} & \cdots & y_{2N+1} \\ y_2 & \cdots & y_{N+1} & y_{N+3} & \cdots & y_{2N+2} \\ \vdots & & \vdots & \vdots & & \vdots \\ y_i & \cdots & y_{N+i-1} & y_{N+i+1} & \cdots & y_{2N+i} \\ \vdots & & \vdots & \vdots & & \vdots \end{bmatrix}$$

and W is a diagonal weighting matrix with $w(i)$ along the diagonal. Both the steps of EM algorithm are repeatedly

executed until value of $\vec{\alpha}$ gets stabilized.

2.5 Rotation Tolerant Resampling Detection

While Propescu et al [9] resampling detector is tolerant to rotation, Prasad et al [1] & Galhagar's [8] detector was not tolerant to rotaion. R. Quain et al [10] used energy spectrum to propose rotation-tolerant resampling detection based on Gallghar's method [8]. They divided suspicious image into $N \times M$ subimages. For each subimage they calculated energy

spectrum of $\left[i * N / k \right]^{th}$ row independently for $i=0,1,2,\dots,k$ where $k = \left\lfloor \frac{1}{3} N \right\rfloor$.

Due to various distortions in image it is possible that two sub-images will have peak position at little different positions. They resolved this issue by quantizing energy spectrum using peak position of each spectrum & calculated distance between subimages in term of resampling rate pattern. They used this resampling rate pattern to classify image. Range & step were two important parameters of quantizer design. For example, a quantizer with range R and step size s divides positive real numbers into the following groups:

$$\begin{aligned} & \frac{R}{s} \times s, \infty \\ (0, s) \ [s, 2s) \ [2s, 3s) \dots \ [\frac{R}{s} \end{aligned} \quad (11)$$

Peaks that fall into the same group were quantized to the same value.

3. RESAMPLING DETECTION ON JPEG IMAGES

JPEG is the widely used image format. Often digital images are compressed with JPEG before distribution. Often forgery of image is followed with JPEG compression. The compression acts as a noise source, making the detection of interpolation more difficult. A JPEG compressed image contains one DC level for each 8×8 pixel block of the image. In the decoding process, this DC level is used (in conjunction with the AC coefficients of the DCT) to reconstruct the image. In the absence of the non-DC coefficients of the DCT, JPEG decoding has an effect similar to nearest neighbor interpolation. This introduces periodic patterns which interfere with the periodic patterns introduced by re-sampling [1]. Hence, the current re-sampling detectors are able to detect re-sampling only up to a JPEG QF of 95 [1][9].

3.1 Adding Noise to suppress JPEG blockiness

JPEG is a lossy compression scheme. If the original image is in an uncompressed format, information is lost when it is converted

to JPEG. As quantization is irreversible getting back original uncompressed image in any case is not possible but it is possible to make statistics of compressed image equivalent to original image by adding noise. L. Natraj et. al [11] proposed a simple method to suppress the JPEG artifacts by adding noise to the image pixels. While doing so, the periodic patterns due to re-sampling were not completely lost while the JPEG patterns almost disappear. However, while adding noise care is to be taken on the amount of noise that is added. If the Signal to Noise Ratio (SNR) is high, then it may not be enough to suppress the JPEG artifacts. If the SNR is too low, then it would also destroy the re-sampling patterns.

To analyze this further, they considered the problem of identifying whether a given bitmap image was previously JPEG compressed. After adding noise though amplitude of periodic patterns due to scaling were decreased but they were present in image while JPEG periodic artifacts were suppressed. Magnitude of noise to be added to remove periodicity of JPEG compression was a significant phase of their experiment as adding too much noise may also suppress the periodicity of re-sampling patterns. From their experimental results it is found that for a moderate level of JPEG compression (QF 75-90), Gaussian/Uniform noise in the SNR range of 28-24 dB works well for different re-sampling operations and adding further noise destroys the re-sampling patterns. For lower QFs (QF 50-75) however, up-scaling can still be detected and the noise to be added can go up to an SNR of 20 dB.

3.2 Recompressed Resampling Detection

M. Kirchner & Gloe [3] found that a block-wise quantization will decrease the variance of the prediction error of pixels within a block and increase it for pixels near the block borders. As a result, it will have additional distinct peaks at frequencies $(k/8, l/8), (k, l) \in \mathbb{Z}^2$. In case of a geometric transformation, these JPEG peaks underlie the affine transformation mapping, similar to the resampling peaks. Also resampling affects the shape of the 8×8 block structure and hence shifted versions of the JPEG peaks occur in the p-map's spectrum [9]. As a result, the spectrum of a pre-compressed resampled image's p-map exhibits a mixture of resampling and shifted JPEG peaks. Knowing that resampling yields periodic artifacts in the p-map that are visible as distinct peaks in the p-map's Fourier spectrum, resampling detectors base their decision on some kind of a peak detector. While Popescu and Farid's method employs an exhaustive search over a large set of precomputed synthetic p-maps [9], M. Kirchner & Gloe calculated the maximum gradient in the cumulative periodogram to test for the existence of strong peaks more efficiently [3]. Both detectors, however, have weaknesses when precompression come into play. Every peak detector will be sensitive to peaks due to JPEG post-compression. & these peaks must be ignored when searching for resampling peaks. However, it is not possible to simply remove all spectral components at frequencies $(k/8, l/8)$, since the JPEG peaks are spread over a certain range around their theoretical position.

4. PERFORMANCE ANALYSIS

From the above discussion we can say that each kind of digital forgery detection method can solve only one kind of forgery. As this is passive approach some heuristic required before applying specific forgery detection technique.

S. Prasad and K. R. Ramakrishnan [1] used only one image to test the proposed algorithm and didn't provide information about its size or format. Also compared to actual image size forged area was very large which may not exist in actual forgeries. The

major weakness of the method is that it cannot be applied to rotated or skewed images.

As in [1] in [8], A. C. Gallagher also found periodicity in variance function of second order derivative while detecting interpolation in zoomed digital images. Based on the fact that the mentioned periodicity is directly related to the resampling rate, the author easily estimates the resampling rate. The major weaknesses of this method are similar to [1]. The tests were performed on images coming directly from a digital camera, 13 of them were non interpolated but compressed with the maximum quality, and 101 images were the result of using the in-camera digital zoom. Gallagher's detector was verified only on zoomed images so validity of technique in resampled spliced image is challenging question.

In [9], A. C. Popescu and H. Farid have analyzed the invisible correlations brought into the resampled signal by the interpolation step. In order to automatically decide whether signal was resampled or not, Popescu and Farid [9] propose to transform the signal's p-map to the frequency domain using the discrete Fourier transform (DFT). Periodic pattern in the p map yields distinct peaks in the spectral representation. Strength and visibility of the characteristic peaks were enhanced by using a contrast function. The function was composed of a radial weighting window, which attenuates low frequency noise, and a gamma correction step. The detector's final decision was based on the similarity between the p-map of the given signal and elements of a candidate set of synthetically generated periodic patterns. Popescu and Farid [9] gave an empirically derived formula, how to calculate a synthetic map for an affine transformation matrix A . As the detector lacks any prior knowledge about the actual transformation parameters, the detection process involves an exhaustive search in a sufficiently large set A of candidate transformation matrices. For the Popescu's method [9], high computation cost in the iterative computing procedure is required. It takes almost 5 minutes to generate the probability map for the image with resolution 512×512 pixels.

R. Quian et al [10] proposed fast, blind and efficient method capable of detecting traces of arbitrary affine transformation based on periodic properties of the covariance structure of interpolated signals and their derivatives. They claimed that method can be also used for estimating the scaling factors or rotation angles as well as skewing factors. They applied radon transformation to the derivative of the investigated signal. They applied Taylor series to analyze interpolated signal and shown periodic patterns. In comparison to [9] this method works on a much easier principle and is more convenient and faster to implement and run. Another advantage of the proposed method compared to [9] is that it does not need any initialization parameters which selection of which may affect the number of iteration performed. But like earlier methods here also forged area size is comparatively large with respect to background.

Resampling followed by JPEG compression decreases detection performance [9][8] mainly because of two reasons. First, the lossy compression blurs the output signal & second, JPEG compression is based on a 8×8 DCT block-based processing of the image, which can lead to sharp transitions between neighboring pixels at the borders of two consecutive blocks. Both effects may affect prediction error. While subtle periodic traces in resampled images are smoothed out due to smaller prediction errors within a block, new periodic artifacts originating from systematically increased prediction errors at the block borders are introduced. As a result, the magnitude of resampling peaks in JPEG images is generally lower compared to uncompressed images. Also detector must ignore peaks

because of JPEG compression because of which resampling peaks coinciding with JPEG compression peaks will also get neglected.

In [12][14] addition of noise has been studied in the form of Stochastic Resonance (SR) to enhance detection. In [14], Peng et al show how SR noise enhances the detection of micro-calcifications in digital mammograms, which in turn indicates an early sign of breast cancer. In [15], Gaussian noise was used to denoise JPEG images. In [11] on adding controlled noise (by adjusting the noise power), JPEG periodic patterns were suppressed while the periodic re-sampling patterns were partially retained. They further analyzed with Gaussian and Uniform noise and considered various re-sampling operations. They showed that noise added JPEG images behave similar to an uncompressed image. From their experiments, they found that when a series of re-sampling operations are done on an uncompressed image and then saved in JPEG format, scaling can be detected as long as it is the final re-sampling operation.

Toshihiko Yamasaki et al [16] gave very simple approach which can be applied to conventional liner resizing methods such as nearest neighbor as well as to non-linear resizing method such as seam carving. Major drawback of this method is required human intervention in output image before taking any decision of resizing. For the images with quality factor above 80 even in the original JPEG images show lot of irregularity of block boundary. Theoretical analysis of this method is also insufficient. Method is evaluated only on different version of single image of lenna. The detection accuracy is assessed mainly by evaluating the missing detection and false alarm probabilities; in the case of classifier-based detectors, the detection accuracy is assessed by separating the considered image set in a training set and a test set, where the missing detection and the false alarms are directly evaluated.

It is obvious, that the pre-compression JPEG quality is a very influential factor on the detection performance after resampling and post-compression. The stronger the blocking artifacts were, the more they will remain in the processed images. From M. Kirchnar's [3] work, it is advantageous when the pre-compression quality is below that of re-compression because strong JPEG compression causes blurred blocks. It can be observed from their work that low pre-compression as well as high post-compression qualities increase the ability to detect resampling. According to them resampling of re-compressed images is better detectable than resampling of solely postcompressed images. The strength of precompression, which is necessary for a successful resampling detection, however generally depends on the resampling parameters. Compared to up scaling, a detection of downscaling requires a lower JPEG quality in the first compression step. For instance, for a post-compression quality of 90, a pre-compression quality below 50 is required to obtain detection rates comparable to the baseline results. M. Kirchnar concluded that, for re-compressed images, a low JPEG quality not necessarily means a bad detection performance. But since this technique is neglecting peak at $1/8$, $k/8$ frequency, it is not able to detect the resampling at this frequency. Mahdian and Saic [6] improved the technique of [8] by applying Radon Transform to the second derivatives of tested images. Accordingly, it can detect not only rescaled images but also rotated images. The major drawback of the technique is its high false positive rate, especially in detecting images which contain strong textures.

5. CONCLUSIONS

From a forensic point of view most of the current re-sampling detection methods fail on JPEG images. Up scaling is generally

better detectable than downscaling. After JPEG compression, the detection rates considerably drop both for up- and downscaling. Above discussed experimental tests shows if spectral resolution becomes large then a peak detector can better distinguish between shifted and original JPEG peaks (that have to be ignored). But the concept of using shifted peaks for the detection of resampling is not limited to JPEG peaks it can be observed in peaks stemming from color filter array (CFA) interpolation inside the camera [17]. Adding noise to a JPEG image in the pixel domain is an effective pre-processing step before passing the image through a re-sampling detector for forensic analysis. Addition of uniform noise yields superior results when compared with the original re-sampling detector. This makes re-sampling detection possible for moderately compressed JPEG images. Finally, we also find that scaling can be detected as long as it is the final re-sampling operation.

Every existing resampling detector has its pros and cons. most of the experimental tests are performed on a different set of unaltered and interpolated images which do not allow a fair and easy validation and comparison with newly proposed methods. Although all proposed approaches assure good performance, they fail on real life forgeries. As a matter of fact, most of the published works are having same type of forgery for evaluation in different test images such as $n \times m$ size area is forged & reinserted into image. In real life forged area will never have uniform boundary. It remains an open research question if (and how) a more reliable detection of downscaling is possible. Since the results presented in most of the papers are limited to the case of scaling, more research required on examination of additional affine transformations such as rotation. Similarly CFA interpolation inside the camera could disturb the resampling detectors in compressed images. More study in this direction is required.

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