A Novel Method for Block Size Forensics Based on Morphological Operations

Weiqi Luo[1], Jiwu Huang[1], and Guoping Qiu[2]

[1] Guangdong Key Lab. of Information Security Technology
Sun Yat-Sen University, Guangdong, China, 510275
[2] School of Computer Science, University of Nottingham, NG 8, 1BB, UK
isshjw@mail.sysu.edu.cn

Abstract. Passive forensics analysis aims to find out how multimedia data is acquired and processed without relying on pre-embedded or pre-registered information. Since most existing compression schemes for digital images are based on block processing, one of the fundamental steps for subsequent forensics analysis is to detect the presence of block artifacts and estimate the block size for a given image. In this paper, we propose a novel method for blind block size estimation. A 2×2 cross-differential filter is first applied to detect all possible block artifact boundaries, morphological operations are then used to remove the boundary effects caused by the edges of the actual image contents, and finally maximum-likelihood estimation (MLE) is employed to estimate the block size. The experimental results evaluated on over 1300 nature images show the effectiveness of our proposed method. Compared with existing gradient-based detection method, our method achieves over 39% accuracy improvement on average.

Keywords: Block Artifacts Detection, Digital Forensics, Morphological Operations.

1 Introduction

Recent development in digital multimedia processing methods and related software tools such as *Photoshop* has made it increasingly easy for ordinary users to alter (tamper) the contents of multimedia data without leaving obvious traces. As a result, verifying the trustworthiness of multimedia data has become ever more challenging.

Traditional approaches to multimedia security need additional processing at the time of data creation. For instance, watermark based methods need to embed an imperceptible digital watermark in advance in order to facilitate tampering detection at a later time. However, in many real forensics scenarios, there is no additional information such as digital watermark and/or digital signature can be used. Thus those active approaches which need such information would fail in such situations.

Some passive methods [1,2,3,4,5,6] have been reported recently to provide forensics information on how multimedia data is acquired and processed. The

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passive methods exploit inherent traces left by various modules in the imaging device or software system to exposure digital tampering without relying on any additional information. The artifacts left by the past operations performed on the multimedia signals can serve as an intrinsic feature for use in forensics analysis. By extracting and analyzing those inherent features, we can deal with many forensics problems related to source identification and forgery detection.

The block-based processing is widely employed in many well-known encoding mechanisms, and one of the inherent patterns for such data is the block artifact. To our knowledge, most existing works on block artifacts are proposed with the purposes of image restoration and enhancement, only a few are for forensics purposes [7,8,9,10]. It is well known that the block artifact is bad for the quality of the image. However, from the point of view of digital forensics, the block artifact is a useful feature for analyzing the content of the multimedia signal. For example, the authors in [7] proposed a method to determine whether a BMP image has been JPEG compressed previously by detecting the block artifact effects. It has also been shown that JPEG image splicing [8] and MPEG recompression [9] can be exposed based on the block artifacts. In most prior literatures, it is always assumed that the image is compressed by a known scheme such as JPEG, MPEG with a fixed block size of 8×8 or 16×16. However, in many forensics cases, there are many other options of the block size in different source coders, for instance, some vector quantization encoders employ block size as small as 2×2. JPEG 2000 has the option of tiling the image with any block size. Also, the block needs not be a regular square shape. Therefore, given a BMP image without any knowledge of prior processing, is it possible to detect the presence of block artifacts and estimate the block size? This is a crucial question for further forensics analysis such as source coder identification and quantization parameters estimation, because the inaccurate block size estimation would lead to invalid subsequent analysis.

One relevant work that we are aware of is reported in [10]. To estimate the block size, the method first obtains the gradient separately along each dimension, and then averages resulting data along the orthogonal direction and obtain a 1-D average values both in horizontal and vertical directions. By estimating the period of the 1-D signal using maximum-likelihood estimation (MLE), the block size can be estimated. From our analysis and large experiments, we find that detecting the block boundaries by observing the image gradient is very sensitive to the image contents such as edges. How to eliminate the effect of the image content is the key of the detection algorithm. In this paper, we first design a 2×2 cross-differential filter to search the possible positions that are along the block boundaries, and then employ morphological operations to eliminate the effect of the content edges, and finally estimate the block size using MLE. Compared with the gradient-based method [10], our proposed method can achieve over 39% accuracy improvement on average.

The rest of the paper is arranged as follows. Section 2 describes the estimation methodology, including the filter design for locating possible boundaries, block boundaries detection based on morphological operations and block size estimation using MLE. Section 3 shows the experimental results and discussion. The concluding remarks and future works are discussed in the Section 4.

2 Methodology

Block artifacts appear as artificial discontinuities in an image. Since the block-processing in commonly used compression standard is performed regularly on each non-overlapping block with a fixed size, we have following two observations:

- The block artifact boundary just appears in two directions, *i.e.*, horizontal and vertical. Any boundaries occur in other directions should be regarded as false block boundaries.
- For nature images, the lengths of the boundaries along block artifacts should be much longer than those content edges in horizontal and vertical directions.

Based on these observations, we first design a filter to locate all the possible pixels along the block boundaries in an image, and then employ morphological operations to remove the effect of boundaries that are in other directions and short edges along the block artifact directions. The details of our proposed method are described as follows.

2.1 Filter Design for Locating Possible Boundary

In prior literatures, *e.g.* [10,11], image gradient is commonly used for measuring the discontinuities in an image. However, based on large experiments, we find that the gradient-based measurement is very sensitive to the image content such as edges, and thus it is not a good way to detect the block artifact boundaries introduced by compression schemes such as JPEG and MPEG. To overcome these weakness, we first design a 2×2 cross-differential filter to eliminate the effect of the actual image contents, and then obtain a binary image from the filtered image in each dimension for subsequent block boundary detection.

Given an image $f(i, j)$, where $1 \le i \le M, 1 \le j \le N$, we first divide it into 2×2 overlapping small blocks. As illustrated in Fig.1, we consider all the adjacent block pairs in horizontal and vertical directions, respectively.

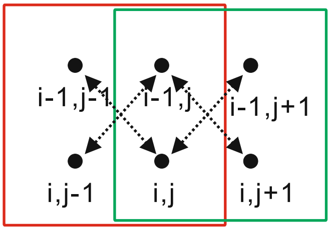
Taking horizontal filter for example[1], for each coordinate (i, j) in the image f, we compute the two cross-differences $\alpha(i, j)$ and $\beta(i, j)$ as follows.

$$\alpha(i, j) = |f(i-1, j-1) + f(i, j) - f(i, j-1) - f(i-1, j)|$$

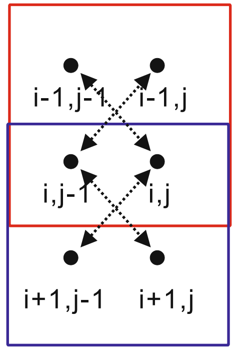
$$\beta(i, j) = |f(i-1, j) + f(i, j+1) - f(i, j) - f(i-1, j+1)|$$

Then we obtain a binary image $f_V(i, j)$ which can indicate the vertical discontinuities in the image f by comparing the two differences α and β,

[1] In the paper, we just show the process of the block size estimation in horizontal direction. We can repeat the process similarly in vertical direction.



(a) Horizontal Filter



(b) Vertical Filter

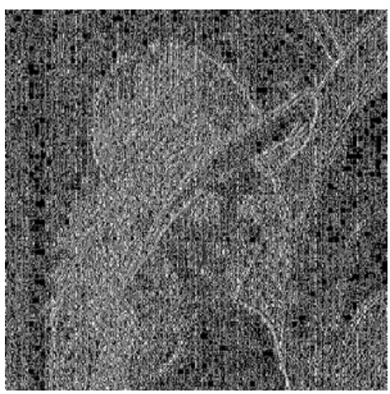
Fig. 1. Filters in two directions

$$f_V(i,j) = \begin{cases} 1 & \text{if } \alpha(i,j) < \beta(i,j) \ \&\ 2 \leq i \leq M, 2 \leq j \leq N-1 \ , \\ 0 & \text{Others.} \end{cases}$$

Fig. 2 shows a test example using the horizontal filter. Fig.2 (a) is a JPEG Lena image in a relative high quality (PSNR=38db) without any obvious visual block effects, Fig.2 (b) is the binary image f_V after filtering. If zoom in, it can be observed that most 8×8 block boundary introduced by compression as well as the edges in image content has been detected.

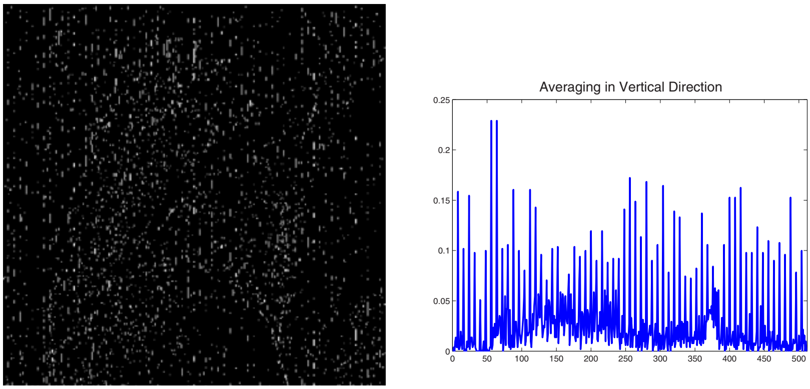
We note that most edges in the image content are not along the vertical or horizontal direction, like the edges of the hat, hair and the shoulder. In next subsection, a structure element is designed and the erosion operation is employed to remove such edges and preserve the long vertical (horizontal) boundary which most likely comes from the block artifacts.

(a) JPEG Lena with $QF = 75$



(b) f_V for Lena

Fig. 2. Vertical discontinuities detection using horizontal filter



(a) Erosion Version of f_V with Se_V (b) Averaging Values in Vertical Direction

Fig. 3. Erosion operation on the filtered Lena image (Fig.2 (b)) and the average values in vertical direction

2.2 Block Boundary Detection Based on Morphological Operations

Mathematical morphology (MM) is a set-theoretical approach for digital signal analysis, and it is widely applied to digital image for the processing of geometrical structures such as boundary extraction, region filling, extraction of connected components and skeletons by locally comparing with a so-called structuring element. Erosion and dilation are the two basic operations of MM. In our algorithm, we employ the erosion operation to detect block artifact.

As mentioned earlier, the artificial boundaries introduced by the block-based processing are arranged regularly in an image. Therefore, after locating all the possible boundaries using our proposed filter and obtaining a binary image f_V, we design a structuring element combining with the erosion operation to eliminate the effect of the edges in the image, such as short edges along vertical (horizontal) direction and/or the bevel edges.
Two structuring elements Se_V, Se_H of size 5×5 are designed as follows.

$$Se_V = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \quad Se_H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

where Se_V, Se_H are the structuring elements for short boundary removal in vertical and horizontal directions respectively.

As shown in Fig.3 (a), most bevel edges in Fig.2 (b) have been removed effectively after erosion operation. The remaining boundaries are most likely coming from the block artifacts. To estimate the horizontal block size, we average the binary values as shown in Fig.3 (a) in vertical direction.

$$A_V(j) = \frac{1}{M}\sum_{i=1}^{M} E_{Se_V} \circ f_V(i,j) \qquad j = \{1, 2, \ldots N\}$$

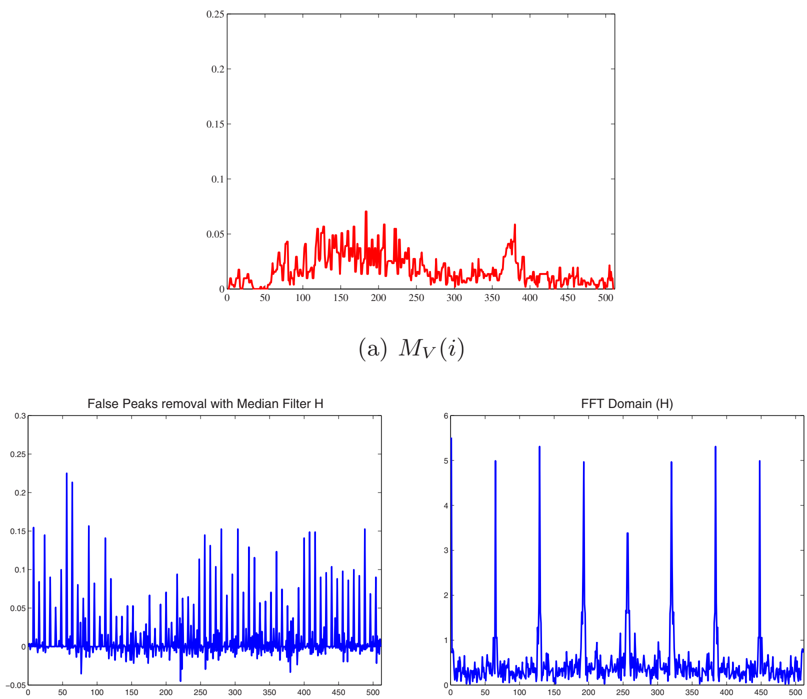
where $E_{Se_V} \circ f_V$ denotes performing erosion operation on the binary image f_V with the structuring element Se_V.

If block processing is present and the block size is B_H in horizontal direction, then the average values $A_V(i)$ will have nearly periodic peaks at multiples of B_H as shown in Fig.3 (b). In next step, we want to estimate the period $\hat{B}_H$ of the average values.

2.3 Block Size Estimation Using MLE

The process of extracting the periodic peak signal (outline) from the average values $A_V(i)$ is similar to the scheme used in [10]. We first perform a median filter with the size 3 on the signal $A_V(i)$ and obtain its median version $M_V(i)$ as follows.

$$M_V(i) = median\{A_V(i-1), A_V(i), A_V(i+1)\}$$



(a) $M_V(i)$

(b) $P_V(i) = A_V(i) - M_V(i)$ (c) Fourier Spectrum of $P_V(i)$

Fig. 4. Illustration of periodic peak signal extraction from A_V

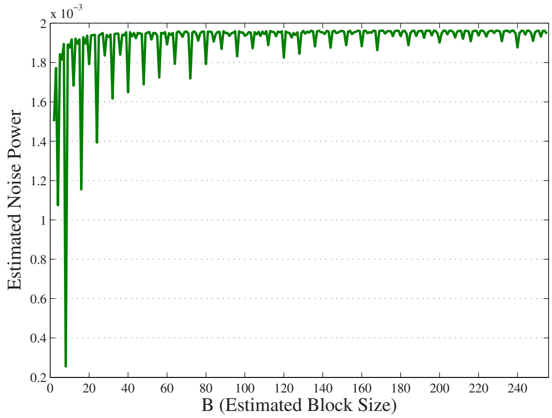


Fig. 5. Noise power $\hat{\sigma}^2(B_H)$ for the periodic signal $P_V(i)$ (Fig.4 (b))

And then we subtract M_V from A_V itself to obtain the approximate outline of the signal A_V.

$$P_V(i) = A_V(i) - M_V(i)$$

In this case, the outline of signal A_V is defined as the average values that are located at the peaks, namely $\{A_V(i)|i = kB_H, k \in Z\}$, and the period of the outline P_V is the estimated horizontal block size $\hat{B}_H$.

Fig.4 (a) is the median version of the average values $A_V(i)$; Fig.4 (b) is the outline of $A_V(i)$. By observing the spectrum of P_V in Fourier domain as shown in Fig.4 (c), we can conclude that the period of P_V is 8, since there are 8 impulses in its Fourier spectrum.

To determine the period from the signal P_V automatically, we use the MLE scheme employed in [12,10]. Suppose P_V consists of a periodic signal s plus an $i.i.d$ Gaussian noise n with mean zero.

$$P_V(i) = s(i) + n(i) \qquad i \in \{1, 2, \ldots N\}$$

where s is a periodic repetition of a signal q with the period B_H:

$$s(i) = q(i \ \ mod \ \ B_H)$$

To estimate the period B_H from the signal P_V, we can maximize the conditional probability density function $p(P_V|s, \sigma^2, B_H)$, where σ^2 is the variance of the noise $n(i)$, B_H is the period of $s(i)$, by minimizing the estimated noise variance $\hat{\sigma}^2(B_H)$ as a function of B_H.

$$\hat{B}_H = \arg\min_{B_H} \hat{\sigma}^2(B_H)$$

Fig. 5 shows the estimated noise power $\hat{\sigma}^2(B_H)$ for JPEG Lena image with quality factor 75 in our example (PSNR=38db). The lowest position in the plot indicates the estimated horizontal block size $\hat{B}_H = B_H = 8$.

3 Experimental Results

UCID (an uncompressed color image database) [13] is a benchmark dataset for image retrieval. In our experiments, we use the UCID (version 2) for test. The database includes 1338 nature images with the size of 352×512 or 512×352. We first convert the color images into gray-scale images, and then simulate the JPEG compression scheme to create the test images with different block size and quality. The process are as follows.

– Resize the 8×8 basic table in JPEG as below by Bi-linear interpolation to obtain basic quantization matrices with different size. This is a reasonable method, because the resizing operation can preserve the order of quantization steps, *i.e.*, larger steps for high-frequency coefficients and smaller steps for DC/low-frequency coefficients. In the experiment, the sizes we employed are $4 \times 4, 8 \times 8, 16 \times 16, 32 \times 32$ and 64×64.

$$\begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$$

– Scale those basic quantization matrices using a scaling factor just like the quality factor employed in JPEG compression to create the images with different block artifacts quality. In the experiment, the scaling factors are from 50 to 90 with a step 10, and the average PSNR on 1338 images are around $32db$ to $40db$ as shown in Table 1.

The experimental results evaluated on these test images are shown in Fig.6. Obviously, our proposed method can get very good detection results in most cases. On average, our method can achieve 89.16% accuracy, while the gradient-based method [10] just has 50.01%.

It is also observed that the larger the block sizes, the lower detection accuracy we obtain. The reason is that for a given test image, when the block size increases,

Table 1. Average values of PSNR (db) for the test images with different size

QF / Size	50	60	70	80	90
4	32.6	33.5	34.8	36.8	40.6
8	33.1	34.0	35.2	37.0	40.7
16	33.1	34.0	35.2	37.0	40.5
32	33.0	33.8	35.0	36.7	40.3
64	32.8	33.6	34.7	36.4	40.0

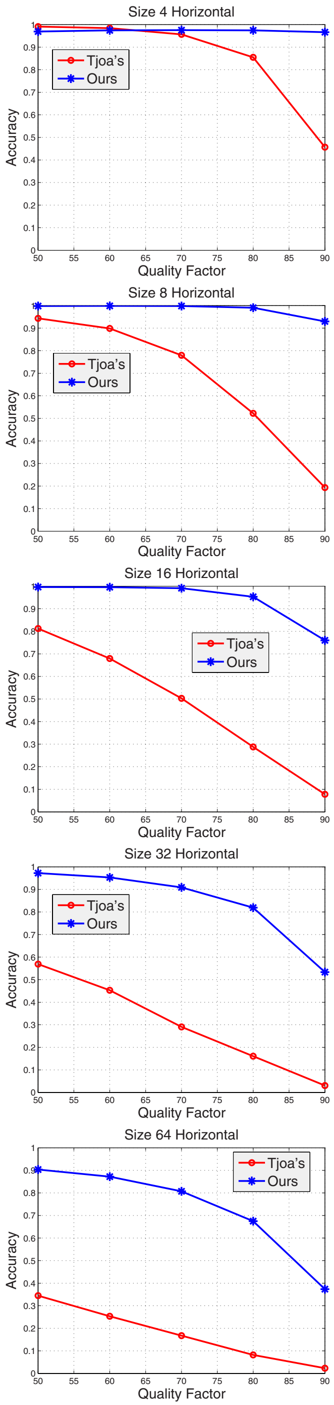


Fig. 6. Compared with gradient-based method [10]

Table 2. Number of blocks in an image with size 512×352

Size of Blocks	4×4	8×8	16×16	32×32	64×64
No. of Blocks	11264	2816	704	176	40

the number of the blocks within an image would become less as shown in Table 2, which means that there are less block boundaries can be used for estimation. Also, when the quality factor increases, the effect of block artifacts would become less. Therefore, the detection accuracy would decrease in both cases.

4 Concluding Remarks and Future Works

In this paper, we propose a novel approach for block size forensics based on the morphological operations. The contributions of the paper are as follows.

- By studying the properties of the block artifacts introduced by image compression, we propose a novel method for block size estimation based on morphological operation. The proposed method can achieve around 40% accuracy improvement compared with existing gradient-based method.
- Propose a 2×2 cross-differential filter to eliminate the effect of the content in an image, and obtain a binary image which can indicate possible boundaries within an image for subsequent block boundary detection.
- Design a structuring element combining with erosion operation to remove the bevel edges in the image and locate the block boundary effectively.

In the future, we will perform more analytic study on why the 2×2 filter work. Moreover, a blind measurement of block artifacts in images based on the morphological operations would be studied. Also, the potential applications of our method in image restoration and enhancement will be investigated.

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