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Solving Time Complexity Issue in Copy-Move Forgery Detection Thru Pre-processing Techniques

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***Abstract*—Copy-move forgery detection (CMFD) has become a popular an important research focus in digital image forensic. Copy-move forgery happens when a region in an image is copied and paste into the same image. Apart from the main problem of detection robustness and accuracy, CMFD is struggle with time complexity issue. One of the options to resolve this problem was by including pre-processing step in CMFD pipeline. This paper reviews the importance of pre-processing step, and existing techniques in reducing time complexity of copy-move forgery detection. An experiment using discrete wavelet transform (DWT) as a pre-processing technique was carried out to evaluate the performance of adopting pre-processing technique in CMFD pipeline. The experimental result has shown a significant reduction in processing time with some trade off to detection accuracy.**

***Keywords*—Copy-move forgery, time complexity, pre-processing, duplicate region detection, discrete wavelet transform**

I. Introduction

Copy-move forgery detection (CMFD) also known as duplication region detection (DRD) is one of the branches in digital image forensic. Copy-move forgery is defined as a forgery where a region in an image is copied and pasted to the same image. It is a very simple forgery process, yet requires a lot of computation time and difficult to detect due to additional modification done to the copied region before being pasted. Modification which involves signal processing attacks, i.e. blurring, noise adding and jpeg compression may reduce the detection rate in many methods however forgery which involve geometrical transform, i.e. rotation and scaling may cause total detection failure [1].

Taking into consideration on the possibility of many types of modification, many researchers proposed towards developing more robust detection methods which could handles those modifications. The results was encouraging, however it creates another problem which is time complexity. Complex algorithm used to get high accuracy detection has leads to high computational time.

Many factors contribute to this problem including the image size, block size, huge number of overlapping blocks, large feature vector dimension, method used in feature extraction and method used in block matching process [2]. Many sorts of techniques have been proposed to solve this issue and one of the solutions was done in the pre-processing phase. This paper highlights the importance of pre-processing step in CMFD, with few available techniques which was adopted in the past. Taking discrete wavelet transform as an example, some explanation and experimental results will also be presented. The rest of the paper is organized as follows. Section II provides brief explanation on copy-move forgery detection process followed by factors to time complexity issue in Section III. Section IV discuss on importance of pre-processing step in CMFD. Section V describes discrete wavelet transform (DWT) as one of the technique in pre-processing step. Initial experimental result and discussion will be presented in Section VI, and Section VII concludes this paper.

II. COPY-MOVE FORGERY DETECTION PROCESS

CMFD techniques are used to authenticate an image by detecting and locating malicious copy-move tampering, if exist. There are two options available in CMFD which are block-based method and keypoint based method. The options are segregated based on how the data is extracted from the image. Most of the CMFD methods proposed by previous research shared the common pipeline which involves 4 important steps including image segmentation, feature extraction, matching and forgery detection. The image segmentation could be done by dividing image into blocks or scanning keypoints in an image. In block-based method, many methods opted to divide image into several overlapping blocks for segmentation of image region. Overlapping blocks, A for image size of MxN and block size is BxB is calculated as;

$$A = (M\text{-}B+1)(N\text{-}B+1) \tag{1}$$

Second step will compute and extract the important features of each block or keypoints and stored in a matrix for matching purpose. In matching process, the arrays of feature set are compared to find similar features. Two feature sets with high similarity is a sign for a duplicated region. The final step is forgery detection where verification is done to reduce the possibility of false matches in the detection image. The final output of this process is the detection map which shows duplicated image region in the image.

III. FACTORS TO TIME COMPLEXITY ISSUE

As the image processing especially image editing software evolve, more manipulations were possible to be done. Forgery is no longer limited to plain copy and then move, instead it involves geometrical transform such as rotation, scaling, flipping, affine transform and etc. before region were pasted to another region in an image. These manipulations were done to adapt and looks coherent with the remaining of the image. Additionally, these manipulations was combined with signal processing attacks or named as post-processing attacks to smoothen any noticeable traces and to complicate forgery to be detected. More post-processing attacks also were taken into consideration such as bright adjustment, color enhancement and in-painting attacks. Earlier researches which handle plain copy-move with JPEG compression, noise or blurring were extended to be able to handle those complicated manipulations.

Robust copy-move forgery detection, which invariant to geometric transformation and signal processing manipulation is highly needed. Unfortunately, robust methods of CMFD lead to higher complexity and processing time. Many factors contribute to this problem including the image size, block size, huge number of overlapping blocks, large feature vector dimension, method used in feature extraction and method used in block matching process [2]. Details reasons to this time complexity issue and previous solutions have been highlighted in [3]. One of the solutions to this time complexity issue was done thru techniques available in the pre-processing phase.

IV. IMPORTANCE OF PRE-PROCESSING IN CMFD

Pre-processing is a first level of abstraction done to the image to improve the image data by suppresses unwanted distortions or enhances some image features important for further processing. There were some argument on image pre-processing which inquired the quality of image after pre-processed, nonetheless, with proper technique and wisdom image pre-processing may solve problems and bring benefits in image feature detection.

In CMFD, pre-processing really help in reducing time complexity with less impact to the detection accuracy. Some previous works are presented to show the importance of pre-processing techniques in CMFD.

A. Previous Works

The first factor to time complexity issue is a huge number of overlapping blocks due to block size and image size. In order to tackle this, key-point based method is implemented as one of the solutions to reduce number of instance blocks. Instead of dividing image into blocks, keypoint-based method scan the whole image and detect high entropy point without dividing the image into blocks [4-8]. However, working with keypoint- based feature has several weaknesses especially when dealing with small size tampered regions. The main drawback is its sensitive to homogenous region, little structure and repetitive object. Inability to detect homogenous region and little structure will result in missed detection (false negative) while showing repetitive structure as tampered region increase false positive result.

In block-based method, some researcher chose to divide image to non-overlapping block instead of overlapping blocks [9]. Using example of formula in (1) for an overlapping blocks, total overlapping blocks to be processed are 6,820,725. In contrast, for non-overlapping blocks, D is calculated as;

$$D = MxN / B^2 \tag{2}$$

For the same example, total number of non-overlapping blocks are 3000x2300/162 = 26,953. Numbers of block to be processed were reduced, nonetheless, it might have affected the accuracy level. Previous works [10] also suggested image resizing during pre-processing step to improve computational efficiency. Nevertheless this process may change some pixels' values and impact the detection result.

The dimension reduction could lower the computation complexity in feature extraction and expedite the sorting and matching processes. Since the features were extracted during feature extraction process, to resolve large feature dimension, enhancements were needed to be done to the feature extraction algorithm itself. As such the solutions were not only to reduce the large feature dimension but also to enhance the method used in feature extraction process.

The basic process in reducing feature vector dimension is by converting a coloured image to grayscale before further analysis [11-15]. This is a popular step during pre-processing stage and usually the first step in CMFD workflow.

Principal Component Analysis (PCA) is a method for simplifying a multidimensional dataset to lower dimension for analysis or visualization. It was first introduced in CMFD domain by [16] to yield a reduced dimension representation. Compared to discrete cosine transform (DCT) [11] which has feature dimension of 256 for 16x16 block size, PCA reduced feature dimension to half of the original size for 8x8 block size. PCA was then used as a tool to reduce the feature vector size which was extracted from the image blocks by many other authors [17, 18].

Other than PCA, Discrete Wavelet Transform (DWT) also has been widely used as method to reduce the dimension of image representation. Li *et al.* [19] and Myna *et al.* [20] reduced the image dimension by taking only the low frequency sub-band of DWT before the Singular Value Decomposition (SVD) is applied to the fixed-sized overlapping blocks. With this approach, feature size is reduced ¼ of its original size. Not only the experimental results demonstrated that the proposed approach decrease computational complexity, but it also localize the duplicated regions accurately even when the image was highly compressed or edge processed. Works by [15, 21] DWT for the same reason.

Zimba and Xingming [22] used an improved Discrete Wavelength Transform (DWT) together with PCA Eigenvalue Decomposition (PCA-EVD) in their works. They improved time complexity by reducing the feature vector to 8. In [23] Zimba enhanced his previous works to increase robustness and reduced time complexity by extracting features from all the four sub-bands of DWT, applied PCA-EVD, adopted radix-sort and finally applied SATS to verify duplicated. The proposed algorithm was claimed not only fast but also more robust compared to the algorithms proposed by [24, 25].

[14, 26] used SVD not only to extract unique feature vectors of image blocks, but also to reduce blocks features dimension and increase resistance of noise. Before applying SVD, Yang & Huang transformed image to grayscale and further down sampled image to lower resolution of 128x128. Only the first component of the sv-vector for each block is chosen to be used for matching process. With this sorting complexity and memory space was reduced dramatically. In 2013, after applying 2D-DCT to each block to generate the quantized coefficient, [12] used SVD to extract only the largest singular value from each quantized block to reduce the feature dimension. With this approach, feature size also was reduced ¼ of its original size.

[27-29] proposed adopting Gaussian pyramid decomposition to reduce the image size. Sub-image in low frequency which produced by this process is chosen to reduce the complexity of the detection algorithm and help to improve the detection result when there are some post-processing operation such as JPEG compression and noise contamination. In his works, image is first reduced in dimension by Gaussian pyramid, before the blocks' features were extracted. Fig. 1 gives the illustration about Gaussian pyramid decomposition used by [28].

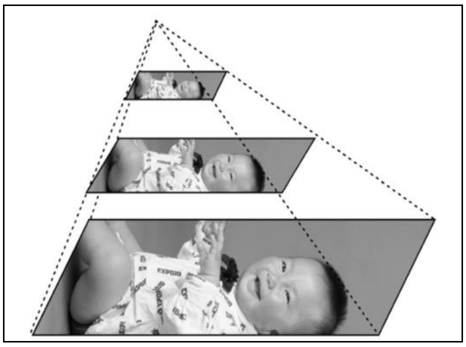

Fig. 1. The illustration of Gaussian pyramid decomposition [28]

Hu moment was applied to the fixed sized overlapping blocks of low-frequency image in [27, 28] while in [29] mean of image pixel value in each circle region were calculated and adopted as features. Apart of that, to further reduce the computational complexity, only the first four moments and four features of the circle block were used as the feature for above works respectively.

Apart of that, low-pass filtering also adopted during pre-processing stage by few researcher to improve the detection performances, especially in the case of signal processing attacks. By adopting low-pass filtering, high frequency disturbances or smooth image modification were alleviated thus giving a better detection result [30]. Li *et al*. utilized Gaussian low-pass filter in both works [13, 31] and followed by other researchers [32] for the same purpose.

In summary, many method adopted pre-processing steps in their CMFD pipeline in order to reduce feature dimension, thus lower down the complexity time. These include grayscale conversion, Gaussian pyramid decomposition, applying PCA, DWT or SVD, feature truncation or selection of dedicated features as well as improved DCT. By adopting pre-processing steps time complexity could be reduced in feature extraction and matching process with less impact to the robustness of the detection.

V. DISCRETE WAVELET TRANSFORM

Discrete wavelet transform (DWT) is a popular technique adopted in pre-processing step to reduce time complexity. This method is chosen with respect to the following criteria:

- Able to reduce the image size without losing important information
- Extract the good frequency resolution for low-frequency component
- Reduce the number of instance blocks effectively

Using wavelet analysis, image information is divided into approximate and detail sub-signal. The approximate sub-signals provides general trend of pixel values while three detail sub-signals are on the horizontal, vertical and diagonal details also extracted. Hard thresholding and soft thresholding could be applied to achieve filtering and compression to the image.

Fig. 2 shows the basic decomposition steps for images using DWT while Fig. 3 describes the reconstruction steps of image. From the fig. low-pass filter is named as Lo_D while high-pass filter is Hi_D. Low-pass filter is use to get the approximate values while high-pass filter is use to get the details signal values.

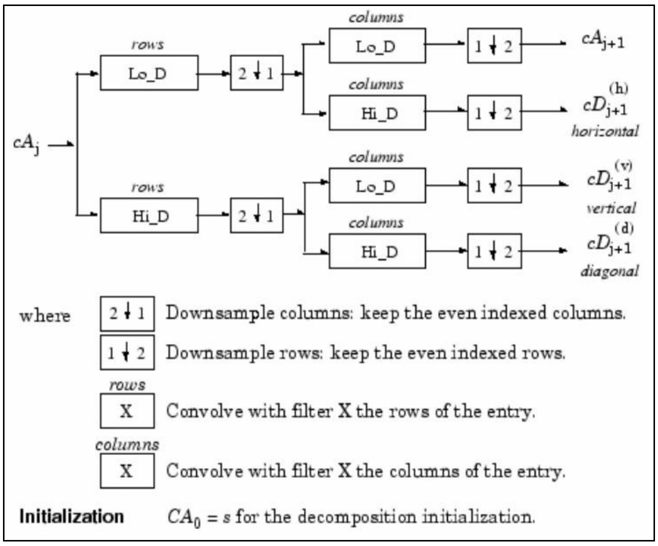

Fig. 2. The 2D-DWT decomposition steps

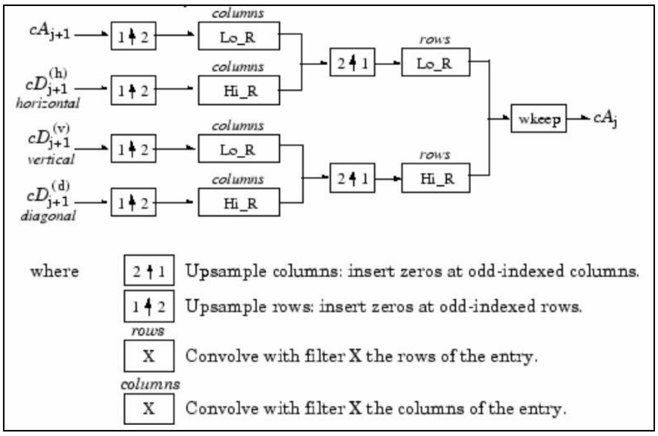

Fig. 3. The 2D-DWT Reconstruction steps

Given a signal which put through low-pass filter and high-pass filter, followed by dyadic decimation, it will produces two sets of coefficients: approximation coefficients *cA1*, and detail coefficients *cD1*. Then, the approximation coefficients *cA1* is splits in two parts using the same scheme, and producing *cA2* and *cD2*, and so on based on the level *j*. Using 2-D DWT approximation coefficients at level *j* is decompose into four components which is the approximation at level *j* + 1 and the details in three sub-signals (horizontal, vertical, and diagonal). Fig. 4 shows the resulting decomposition of an image.

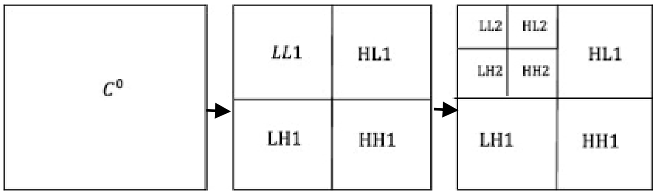

Fig. 4. The The resulting decomposition of image

Since the approximate or low frequency (LL) sub-signals consist most of the image energy, it will be used as an input in feature extraction instead the original image. This will reduce the size of processing to only ¼ of the image.

VI. EXPERIMENTAL SETUP AND RESULTS

An experiment is design to evaluate the efficiency of adopting pre-processing technique in CMFD pipeline. Fig. 5 illustrated the experimental design of this CMFD process. Further explanations are given in the next section.

A. Experimental Setup

The experiment is run in MATLAB R2013b using Comofod dataset with image size of 512x512. DWT decomposition are opted to be used in the pre-processing steps. Image is divided into 16x16 overlapping blocks, assuming that the size of duplicated region is bigger than the block size. Zernike moments is used in this experiment to extract the robust features of blocks. Details of the experimental steps are as follow:

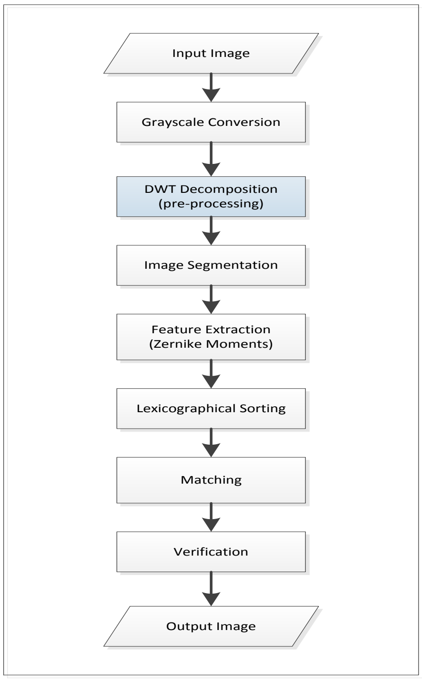

Fig. 5. The Experimental Design

1) Grayscale conversion: since dataset consist of RGB image, image is first convert to grayscale image.

2) DWT decomposition: Grayscale image then decompose into 4 sub-band [LL, HL, LH, HH] using DWT. Only approximate sub-signals (LL) is used for next process.

3) Overlapping blocks: sliding window operations to produce overlapping blocks is done to the low-frequency (LL) only.

4) Feature extraction: calculate each block using Zernike Moment feature extraction methods and store to a vector.

5) Lexicographical sorting: Vector is then sort lexicograpical order for next computation.

6) Compute offset: For each pairs of rows vector, calculate the offset value $(\Delta x, \Delta y)$.

7) Matching: for all $(\Delta x, \Delta y)$>Threshold, marks the blocks.

8) Verification: If the marked blocks are adjacent, it might be part of duplicate region.

9) Final image: Original and detected forged image will be shown as final result.

B. Experimental Result

Experiment was done using Zernike moment as feature extraction. Fig. 6 (a)-(c) and Fig. 7 (a)-(c) shows the original image, tampered image and detection result respectively without DWT as pre-processing.

Fig. 6. (a) Original image (b) Tampered image (c) Detection result

Fig. 7. (a) Original image (b) Tampered image (c) Detection result

Fig. 8 (a)-(c) and Fig. 9 (a)-(c) on the other hand, shows the similar set as previous Fig. 6 and Fig. 7 but with DWT adopted in pre-processing stage.

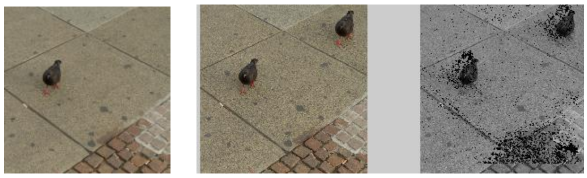

Fig. 8. (a) Original image (b) Tampered image (c) Detection result

Fig. 9. (a) Original image (b) Tampered image (c) Detection result

From the above examples, we could see that the accuracy level has dropped once DWT was applied to the CMFD pipeline. Since morphological process was not implemented in this experiment, a lot of noise was shown.

TABLE I. PROCESSING TIME

Picture Label	Without DWT	With DWT
Birds	519s	234s
Building	520s	230s

Table I shows the processing time taken to complete one cycle of CMFD in this experiment. Looking to the processing time, time taken to complete CMFD cycle was reduced by more than half upon adopting DWT in pre-processing stage. Since this is only an initial result, it is indeed provides a promising result for further enhancement in the CMFD process.

VII. Conclusion

Copy-move forgery detection is a part of digital forensic domain. Apart of trying to achieve high detection accuracy, the capability to produce result in near real-time is highly needed. Thus, many methods have been proposed to resolve this issue and one of the options is through implementing pre-processing technique. Experimental result shows that time complexity could be reduced using suitable pre-processing techniques with some price to detection accuracy. This however could be prevented by implementing post-processing techniques to remove the noise. There are still many works to be done in CMFD in order to achieve an efficient and accurate detection result.

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