PASSIVE DETECTION OF COPY-MOVE FORGERY USING WAVELET TRANSFORMS AND SIFT FEATURES

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Abstract: Image forgery is a major issue today in publishing and printing. Several images are morphed before publishing in order to incorporate extra information. The problem becomes more complicated with different means of image capture. There exist a variety of cameras with different resolutions and encoding techniques. Many times the forged image is compressed or resized before publishing. Detecting forgery in such cases is a challenging task. Different techniques of tampering include resizing, blurring, compression, addition of noise, image splicing etc. The most common type of digital image forgery is copy-move forgery. In this paper, a passive technique for detecting copy-move forgery based on wavelet transforms and SIFT features is proposed. The wavelet transforms employed are Discrete Wavelet Transform (DWT) and Dyadic Wavelet Transform (DyWT). The image is divided into four sub-bands viz. LL, LH, HL and HH by the wavelet transform. Since the LL sub-band contains most of the information, SIFT is applied on the LL part only, to extract the key features and find descriptor vector of these key features and then find similarities between various descriptor vectors to conclude that the given image is forged.

Keywords: tampering, wavelet transforms, copy-move forgery, scale invariant feature transform (SIFT), dyadic wavelet transform

I. Introduction

Since the invention of photography, images have been retouched and manipulated. Now-a-days the adage ‘seeing is believing’ does not hold. In the last decade, large amount of digital image data was manipulated in papers, tabloids, fashion magazines, court room videos etc. Detection of image forgery is a challenging task due to various methods of tampering the image and a large number of distinct image capturing devices available. Most of the forgery detection techniques are categorized into two major categories: active and passive. Active methods, also known as non-blind/intrusive methods, require some information to be embedded in the original image when the image is captured. Due to this pre-requisite, active methods have limited scope. Some of the examples of these methods are watermarking and use of digital signature of the camera. All cameras don’t possess this feature. Passive methods, also known as non-intrusive/blind methods, don’t require any information to be embedded in the digital image. A digital image can be forged by various attacks like rotation, scaling, resizing, addition of noise, blurring, compressing, image splicing, copy-move etc. In copy-move attack, a part of image is copied and pasted in a different area of the same image. The ease of copy-move forgery makes it the most common forgery that is used to alter the content of an image [14]. Usually the forger forges the image with an intention of hiding some object by covering it with an image segment that is copied from the same image. For example, a photograph of a crime scene may be tampered with, by hiding critical data. Another reason of copy-move forgery may be to add extra information to the image. For instance, images of political rallies are manipulated to show more number of attendees. A popular example of copy-move forgery is shown in figure 1. In the original image, there were just three missiles. This image was manipulated to show four missiles by copying and pasting one of the missiles in the same image. In this type of forgery, since the image-patch comes from the same image, the color-palette and noise components are mostly similar to the original image. Requirements of a good copy-move detection algorithm are:

- The algorithm must detect an approximate match between small image patches. A common assumption of copy-move detection algorithms is that the forged part is a connected component rather than an aggregation of pixels.
- It must not be computationally complex and must detect a forged image correctly as forged and an authentic image correctly as authentic.

Figure 1. Example of Copy-Move Forgery

MIR Labs, USA
II. Related Work

The distinguishing feature of copy-move forgery is that the copied patch and the pasted patch are the same. Hence one method of forgery detection is exhaustive search [15]. However this method is not feasible due to its computational complexity. Also, there are chances that the copied part is processed upon further by noise addition, geometric distortion and filtering. This increases the complexity. However the correlation introduced between the copied and pasted area is the basis of most detection algorithms. Only passive detection algorithms [12] are discussed here. Birajdar et al. [20] has summarized all the passive techniques for digital image forgery detection. Al-Qershi et al. [25] addressed key issues in developing a robust copy-move forgery detector. Qazi et al. [26] presents a comprehensive study of blind methods for forgery detection. Fridrich et al. [5] introduced a block matching method based on Discrete Cosine Transform (DCT). In this method, the image was divided into overlapping blocks and quantized DCT coefficients of image blocks were used as features. Lexicographical sorting was then performed and copied regions were outputted, based on the similarity of features. Major advantage of using DCT is that most of the energy is concentrated in first few DCT coefficients and most of the other coefficients are zero. Thus changes in high frequency region like noise addition etc. won’t affect the detection procedure. Popescu et al. [4] proposed a similar method as that of Fridrich’s. This method utilized Principal Component Analysis (PCA) for dimension reduction. Number of features generated is half of that of Fridrich’s thus establishing it to be a better method. Drawback of this method is that it fails when the copied region is re-sampled through rotation or scaling. Li et al. [6] devised a sorted neighborhood method based on Discrete Wavelet Transform (DWT) and application of Singular Value Decomposition (SVD). Though the overall process speeds up due to reduction in dimension by DWT, this method is very computationally complex since calculation of SVD takes a lot of time. Bayram et al. [19] introduced a detection method based on Fourier Mellin Transform (FMT). Hao-Chiang Hsu et al. [10] proposed copy-move forgery detection by detecting the similarity using feature extraction by Gabor filter. Leida Li et al. [8] devised a method for copy-move forgery detection using Local Binary Patterns. M.Qiao et al. [9] used curvelet statistics for detection of copy-move forgery after dividing the image into several overlapping blocks. Local visual features like SURF, SIFT, GLOH are robust to several geometrical transformations like rotation, occlusions, clutter and scaling. Hence they are being extensively used for image forgery detection. Hwei-Jen Lin et al. [11] proposed fast copy move forgery detection using block based algorithm with radix sort for improving computational efficiency. But this algorithm is only suitable for resisting JPEG compression and Gaussian noise attacks. Amerini et al. [7], deals with detecting copy-move forgery using a SIFT based method. SIFT is invariant to resizing, rotation etc. Muhammad et al. [21] proposed an efficient copy-move forgery detection method undecimated Dyadic Wavelet Transform (DyWT).

III. Proposed Technique

What can be concluded from the above discussion is that primary advantage in using DWT is reduction in dimension(less number of features) and the primary advantage in using SIFT is its robustness. The proposed method combines the two to give an optimal solution. The method can detect an image as forged even if the copied part is rotated or scaled and then pasted. First the test image is converted into grayscale format if it is in RGB format. The technique gave similar results for both RGB and gray-scale images. DWT is applied on the image (up to level 1). The image gets divided in to 4 sub-bands- LL, HH, LH and HL. Then SIFT is applied to the LL part only. SIFT was used to extract strong or key features from the image. A search is performed for occurrence of same features at different locations in the image. Image blocks that return similar SIFT features from all four images are marked as forged regions. The block diagram of the technique is illustrated in figure 2. Further DyWT was used in the technique. This improved results to an extent. When the image was transformed using DyWT, the key-points found were greater. The method was tested using the MICC-F220 database [7]. Database of forged colored images released by Institute of Automation, Chinese Academy (CASIA) was also used.

![Figure 2. Proposed Technique](image-url)
A. Discrete Wavelet Transform (DWT)
DWT is a linear transform that operates on a vector whose length is an integer multiple of two, while separating the data vector into different frequency components. The process of one dimensional DWT is shown in figure 3. ‘h’ and ‘g’ denote low-pass and high-pass respectively. Output of low-pass filter (after factor two down-sampling) is the approximation coefficients and the output of high-pass filter (after factor two down-sampling) is the detail coefficients or wavelet coefficients. It is the output of the low-pass filter which is used for the next level of transform. Outputs of the two filters (after the down-sampling) are given by (1) and (2).

\[
\begin{align*}
    a_{j+1}[p] &= \sum_{n=-\infty}^{+\infty} h[n-2p]a_j[n] \\
    d_{j+1}[p] &= \sum_{n=-\infty}^{+\infty} g[n-2p]a_j[n]
\end{align*}
\] (1)

(2)

2-D DWT is similar to 1-D DWT. DWT is performed first for all the image rows and then the image columns.

\[
\begin{align*}
    c^{j+1}[n] &= \sum_{k=-\infty}^{+\infty} h[k]c^{j}[n+2^j.k] \\
    d^{j+1}[n] &= \sum_{k=-\infty}^{+\infty} g[k]c^{j}[n+2^j.k]
\end{align*}
\] (3)

(4)

After inserting \(2^j-1\) zeros in \(h[k]\) and \(g[k]\), the filters obtained be \(h^{j+1}[k]\) and \(g^{j+1}[k]\) respectively. The algorithm [23] is described below:

- At \(j=0\), \(I = I^0\).
- Obtain the coefficients at \(j=j\)
- Filter \(I^{j+1}\) with \(h^{j+1}[k]\).
- Filter \(I^{j+1}\) with \(g^{j+1}[k]\).

1-D DyWT is shown in figure 5. Figure 6 shows the DyWT decomposition of an image.

B. Dyadic Wavelet Transform (DyWT)
DWT is not optimal for data analysis. To overcome this shortcoming, Mallat and Zhong [22] introduced the DyWT. There is no down-sampling in DyWT like in DWT. Size of the image is reduced at every level by DWT. But by using DyWT, the size of the image remains same. At each level the image is divided in 4 sub-images. They are labelled as LL, LH, HL, and HH. Let \(I\) be the image. Let \(h[k]\) be the low-pass filter and let \(g[k]\) be the high-pass filter. Starting at \(j=0\) and \(I = I^0\), arrive at the coefficients (at \(j=j\)) using the equations below.

The 2-D DWT process is shown in figure 4. Wavelet decomposition up to 1 level is shown. The image is reduced in to 4 sub-images at each level which are labeled as LL, HL, LH, and HH. Most of the data is concentrated in the LL sub-image and it is considered as the approximation of the image. It represents the coarse level coefficients of the original image. It is the LL sub-image which is decomposed in to four sub-images at the next level. Size of the image is reduced at every level by the DWT transform. This means lesser data to compute since reduction in the size of the image at each level is achieved. For example, a square image of size \(2^n \times 2^n\) is reduced to a size of \(2^2 \times 2^2\) at the next level. Haar DWT was used in the proposed method [3].
C. Scale Invariant Feature Transform (SIFT)

In any image there are a lot of points of interest which can be extracted to provide feature description of the image. The SIFT algorithm can be used to locate a particular object in an image which contains many different objects. SIFT algorithm provides a set of features which do not get modified even by scaling or rotation. Another distinct advantage is that the SIFT is very resilient to noise in the image. A four stage filtering approach is used in the SIFT algorithm [1].

1) Space Scale Extrema Detection

In this step points which can be identified from different views are located. The most efficient way is by using a Gaussian space-scale function. The scale space is defined by

\[ L(x, y; \sigma) = G(x, y; \sigma) * I(x, y) \]  

\[ D(x, y; \sigma) = L(x, y; k\sigma) - L(x, y; \sigma) \]  

2) Key point localization

This stage eliminates those key-points which have poor contrast. This is done by applying the Laplacian operator on the points found in the previous stage. If the value of this function lies below a certain threshold then this value is excluded. This eliminates points of low contrast. The method to eliminate a poorly localized pixel along the edge is described next. There is a large principle curvature across the edge but a small curvature in a perpendicular direction in DoG function. Key-points in the image are found by the Difference of Gaussian (DoG) technique. This technique was proposed by Lowe et al. [1]. DoG is given by (6). This function is compared with its eight neighbors on the same scale and with nine neighbors up one scale and down one scale. It is a point of extrema if it is minimum or maximum among all these 26 values [18].

3) Assignment of orientation

In this step every key-point is assigned an orientation based on the local image properties. The steps are as follows:

a) Calculate the Gaussian smoothed image L by the scale function described above.

b) Calculate the magnitude gradient \( m \) and the orientation \( \theta \) as in (7) and (8).

\[ m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \]  

\[ \theta(x, y) = \tan^{-1}\left(\frac{L(x, y+1) - L(x, y-1)}{L(x+1, y) - L(x-1, y)}\right) \]  

c) An orientation histogram is formed from gradient orientations of sample points. Peaks in histogram are located and using these peaks and any other peaks 0.8 times those of the highest peak are used to create an orientation.

It is possible that a key-point may be assigned multiple orientations.

4) Key point descriptor

Key-point descriptors are created by using the local gradient data used above. The gradient information is rotated so as to align it with the orientation of the key point and then weighted by a Gaussian function of variance \( 1.5 \times \) key-point scale [13]. This is used to create a set of histograms over a square whose center is the key point. Usually a set of 16 histograms each with 8 elements is used by the key point descriptors. This results in the feature vectors having 128 elements. These feature vectors are then used to identify possible objects in the digital image.

IV. Comparative Study

A. Detection based on DyWT

Muhammad et al. [24] proposed a detection algorithm based on DyWT. What the algorithm did was divide the image into 4 sub-images based on DyWT. Then the LL region is further divided into overlapping blocks and matching between similar features is done. In the HH region on the other hand, dissimilarities are checked on the basis of Euclidean distance. This algorithm is not robust to rotation and scaling attacks.

B. Detection based on DWT and SIFT

Forgery detection using SIFT was already performed. SIFT is invariant to geometrical attacks. The authors have implemented forgery detection based on DWT and SIFT. DWT is a multi-resolution technique which can extract strong corners and edges perfectly.

C. Detection based on DyWT and SIFT

This algorithm too is based on DyWT. Since Dyadic Wavelet Transform is not affected by shift, it represents the image information in a better way than the Discrete Wavelet Transform. Key features are extracted by combination of DyWT, SIFT and the RANSAC algorithm. There are many advantages of this method over the previous ones. Firstly, this algorithm is robust to attacks like geometrical transformation, resizing and any combination of these. Secondly, the key features extracted by this algorithm were more than those extracted by the detection algorithm based on DWT and SIFT.

V. Results

A. Performance parameters

Before presenting the results, a few parameters are defined. They measure the performance of algorithms, hence called performance parameters. Performance of any system can be measured in terms of sensitivity, specificity and accuracy. Sensitivity relates to the ability of the algorithm to detect a forged image correctly as forged. It is also called as recall. Specificity relates to the ability of the algorithm to identify an authentic image correctly as authentic. Hence a high value of sensitivity and specificity are required for better performance.
Passive Detection of Copy-Move Forgery using Wavelet Transforms and SIFT Features

of the system. Precision is the probability of truly detecting a forgery. It is also known as Positive Predictive Value (PPV). A few terms are first defined.

TP (True Positive): Forged image identified as forged
FP (False Positive): Authentic image identified as forged
TN (True Negative): Authentic image identified as authentic
FN (False Negative): Forged image identified as authentic

\[
sensitivity = \frac{TP}{TP + FN} \quad (9)
\]

\[
specificity = \frac{TN}{TN + FP} \quad (10)
\]

\[
accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)
\]

\[
PPV = \frac{TP}{TP + FP} \quad (PPV: \text{Positive Predictive Value}) \quad (12)
\]

\[
NPV = \frac{TN}{TN + FN} \quad (NPV: \text{Negative Predictive Value}) \quad (13)
\]

\[
FPR = 1 - specificity \quad (FPR: \text{False Positive Rate}) \quad (14)
\]

\[
FNR = 1 - sensitivity \quad (FNR: \text{False Negative Rate}) \quad (15)
\]

B. Detection based on DWT and SIFT

All computations were performed on a machine with 4 GB RAM and an Intel Core i5 processor. The software used was MATLAB R2012a. 2000 images were tested using the proposed method. 1000 of the images were forged and 1000 were original. For the image shown in figure 7, 325 key-points were found and a total of 22 matching features were detected. The time required for computation was 2.893 seconds. It was found that smaller the size of the test image and the copied part, lesser were the number of features found. Average time of computation was 2.1 seconds.

Table 1. Results obtained with DWT and SIFT

<table>
<thead>
<tr>
<th></th>
<th>Authentic</th>
<th>Tampered</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>1000</td>
<td>1000</td>
<td>664</td>
<td>982</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>18</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>336</td>
</tr>
</tbody>
</table>

Table 2. Performance of the system

<table>
<thead>
<tr>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
<th>FPR</th>
<th>FNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.664</td>
<td>0.982</td>
<td>0.823</td>
<td>0.018</td>
<td>0.336</td>
</tr>
</tbody>
</table>

C. Robustness to different attacks

Robustness of the algorithm was checked by testing images where the copied part was rotated or scaled or both and then pasted. Images tested with various attacks and the results obtained are demonstrated in figure 8. Table 3 gives the key-points, matches detected and time required for computation with different types of attacks. The computational complexity with or without any attack remains the same, proving the robust nature of the technique towards various attacks. However the number of matching features detected was maximum when the copied area was pasted without any rotation or scaling.

Figure 7. (a)Original image, (b) Tampered image, (c) DWT of the image, (d) Matching of similar features

Figure 8. (a)Without rotation or scaling, (b) Scaling, (c) Rotation, (d) Rotation and scaling
D. Comparison with existing techniques

Accuracy of various methods and the proposed method was compared. Zhang-2008[16] achieved an accuracy of 77.32% with the tampered region size 64x64. The method proposed by Popescu-2004[4] managed an accuracy of around 90% for a tampered block size of 128x128 in an image of size 512x512 and JPEG quality factor of 85. Li-2009[17] was able to manage an accuracy of 47.21%. However this low value of accuracy was compensated by high values of sensitivity and specificity. The proposed method achieved an accuracy of 82.30% with 1000 forged and 1000 authentic images.

<table>
<thead>
<tr>
<th>Type of attack</th>
<th>Key-points found</th>
<th>Matches detected</th>
<th>Computation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without rotation /scaling</td>
<td>366</td>
<td>28</td>
<td>0.77</td>
</tr>
<tr>
<td>Scaling</td>
<td>381</td>
<td>19</td>
<td>0.88</td>
</tr>
<tr>
<td>Rotation</td>
<td>370</td>
<td>20</td>
<td>1.04</td>
</tr>
<tr>
<td>Rotation and scaling</td>
<td>380</td>
<td>22</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Table 3. Robustness to various attacks

E. Detection based on DyWT and SIFT

The complete detection process is shown in Figures 10(a), 10(b), 10(c) and 10(d). 10(a) is the tampered image. 10(b) represents the DyWT of the image. Only the LL part is shown in 10(c). Feature matching is applied on only the LL part. The matching feature points are shown in 10(d). For the image shown in figure 10, 748 key points were found and the number of matching points was 46. The time required for detection was 0.962806 seconds. The images shown in Figure 11 depict the robust nature of this algorithm. In these images, the copied part is first pre-processed and then pasted. The degree by which the copied part is rotated is also varied. In 11(b) the copied part is rotated by a smaller degree than in 11(c). In 11(f), the copied part was scaled to a lesser extent than in 11(d). The copied part is both rotated and scaled in 11(e). Lesser keypoints and matching features were obtained in this case. As is seen from the figure, forgery in all the cases is getting detected accurately. Thus the algorithm is robust to various scaling and rotation attacks.

F. Comparison between different methodologies

A comparison between detection by SIFT alone, by DWT and SIFT & by DyWT and SIFT is presented below. Performance parameters-precision, recall and FPR are used to compare the three methods. As illustrated by Table 4, the detection algorithm based on DWT and SIFT achieves the maximum
precision. However for a single image, the algorithm based on DyWT and SIFT was found to be more accurate, since it gave larger number of keypoints and matching features. It is also less complex than the method proposed by Muhammad et al. [24], which uses DyWT and block matching. Hashmi et al. [2] covered the algorithm concerning DWT and SIFT.

<table>
<thead>
<tr>
<th>Method</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIFT</td>
<td>745</td>
<td>964</td>
<td>36</td>
<td>255</td>
</tr>
<tr>
<td>DWT+SIFT</td>
<td>664</td>
<td>982</td>
<td>18</td>
<td>336</td>
</tr>
<tr>
<td>DyWT+SIFT</td>
<td>810</td>
<td>900</td>
<td>100</td>
<td>190</td>
</tr>
</tbody>
</table>

*Table 4. Comparison of different methodologies*

<table>
<thead>
<tr>
<th>Method</th>
<th>Precision</th>
<th>Recall</th>
<th>FPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIFT</td>
<td>0.95391</td>
<td>0.745</td>
<td>0.036</td>
</tr>
<tr>
<td>DWT+SIFT</td>
<td>0.97361</td>
<td>0.664</td>
<td>0.018</td>
</tr>
<tr>
<td>DyWT+SIFT</td>
<td>0.89011</td>
<td>0.810</td>
<td>0.010</td>
</tr>
</tbody>
</table>

*Table 5. Comparison of performance parameters*

<table>
<thead>
<tr>
<th>Method</th>
<th>Matching feature points</th>
<th>Computational complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIFT</td>
<td>Intermediate</td>
<td>More</td>
</tr>
<tr>
<td>DWT+SIFT</td>
<td>High</td>
<td>Least</td>
</tr>
<tr>
<td>DyWT+SIFT</td>
<td>Highest</td>
<td>Intermediate</td>
</tr>
</tbody>
</table>

*Table 6. Comparison of complexity*

<table>
<thead>
<tr>
<th>Method</th>
<th>Robustness to scaling</th>
<th>Robustness to rotation</th>
<th>Robustness to noise (AWGN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DyWT+Block matching</td>
<td>None</td>
<td>Less</td>
<td>None</td>
</tr>
<tr>
<td>DWT+SIFT</td>
<td>Average</td>
<td>Intermediate</td>
<td>Low</td>
</tr>
<tr>
<td>DyWT+SIFT</td>
<td>More</td>
<td>More</td>
<td>High</td>
</tr>
</tbody>
</table>

*Table 7. Robustness to different types of attacks*  

**VI. Conclusion**

Various techniques of image tampering were studied. Previous algorithms for copy-move forgery detection were reviewed in this paper. The proposed technique uses both wavelet transform and SIFT. The wavelet transforms used were DWT and DyWT. DWT reduces the image data and further process only relevant information (low frequency information). Robustness was introduced by SIFT. Hence the proposed algorithm detects image forgery even if the copied part is rotated/scaled and then pasted. Overall accuracy was found to be 82.30% with a database of 2000 images (1000 authentic and 1000 forged images). The proposed method gave reasonable values of sensitivity and specificity. Robustness of the proposed algorithm was checked by testing tampered images where the copied part is rotated or scaled and then pasted. The proposed method was compared with the existing methods. A further attempt was made to use DyWT instead of DWT to improve the performance. It was observed that with DyWT, a larger number of keypoints and matching features were found. In future it is proposed to experiment with other feature extractors like SURF etc.

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**References**


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