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Wavelet-Based Multiresolution Features for Detecting Duplications in Images

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Abstract

Duplication of image regions is a common method for manipulating original images using typical software like Adobe Photoshop. In this study, we propose a wavelet based feature representation scheme for detecting duplicated regions in images. This technique works by first applying multi-resolution wavelet decomposition to small fixed-sized image blocks. Normalized wavelet coefficients are then stacked into a vector in an order from lower to higher frequencies. This kind of representation appears robust to block matching. Duplicated regions are then detected by lexicographically sorting all of the image blocks and applying threshold to the desired frequency of the offsets of the block-coordinates. A semi-automatic technique that detects accurate number of duplicated regions is also proposed. Initial experiments with a set of natural images having duplicated regions show impressive results compared to linear PCA based representation.

1. Introduction

Digital images are easy to manipulate and edit due to availability of powerful editing software and sophisticated digital cameras. Some software (like 3DS Max) is so sophisticated that it is very hard to distinguish tampered images from the authentic counterparts. As a result, digital evidences are not yet accepted in real life applications, e.g., for criminal investigation. A common manipulation in tampering with an image is to copy and paste portions of the image to conceal a person or object in the scene. If the splicing is realistic, it is too hard to suspect the presence of any forgery in the image.

In this paper, we present a technique to efficiently detect and localize duplicated regions in an image. This technique works by first applying the multiresolution decomposition by Daubechies wavelet to small fixed-sized image blocks to obtain an efficient representation suitable to block matching. Duplicated regions are then detected by lexicographically sorting all of the image blocks. While there are some other methods for detecting traces of digital tampering in images [7] and [8], we found only two similar approaches, one uses linear PCA [1], while the other [3] uses DCT based representation. However, [1] claims that the PCA based method outperforms the one with DCT based. So we chose PCA based method to compare with our proposed one in the current study. While these methods employ a similar approach, the wavelet-based representation may better capture the discriminating features. The efficacy of the techniques was demonstrated on credible forgeries with natural scene images.

The rest of the paper is as follows: section 2 briefly explains about a fast wavelet decomposition approach and the detail steps of our algorithm that uses wavelet features. Section 3 describes the experimental details and comparative performance with a PCA-based approach, while the study is discussed and concluded through section 4 and 5.

2. Proposed Approach

We proposed a block-based approach for tampering detection. An unknown gray image is first divided into small overlapping blocks. Normalized wavelet signature is obtained from each block. A matrix is then formed using all blocks into rows, which are sorted lexicographically for further processing by algorithm in 2.2.

2.1 Wavelet Signature

In our implementation, discrete wavelet transform [2], [4], and [5] is used. We adopted Mallat's [6] fast 2D pyramid algorithm. The decomposition is performed over a small block (8 x 8) in two levels leading to seven subbands using Daubechies D2 wavelet.

The simplest way to compute 2D discrete wavelet transform (DWT) of an image is to apply one dimensional transforms over image rows and columns separately and down-sampling. This transform decomposes images with an overall scale factor of four, providing at each level one low-resolution subimage and three wavelet coefficient subimages. The 2D wavelet transform performs a spatial/spatial frequency analysis on an image in the lower frequency subbands. The results depend on the type of wavelets on which decomposition is based on, which in turn depends on the filter specifications. At *j=0,* the scale is $2^j = 2^0 = 1$, which is the scale of original image (I_0). Thus at *j=1*, the subimages resulting from the wavelet decomposition can be written by:

$$D_1^0(m,n) = \left[L_x * \left[L_y * I_0\right]\downarrow 2\right]\downarrow 2(x,y), \quad (1)$$

$$D_1^1(m,n) = \left[L_x * \left[H_y * I_0\right]\downarrow 2\right]\downarrow 2(x,y), \quad (2)$$

$$D_1^2(m,n) = \left[H_x * \left[L_y * I_0\right]\downarrow 2\right]\downarrow 2(x,y), \quad (3)$$

$$D_1^3(m,n) = \left[H_x * \left[H_y * I_0\right]\downarrow 2\right]\downarrow 2(x,y), \quad (4)$$

where $*$ and $\downarrow 2$ denote the convolution and down-sampling operations, respectively. Figure 1 shows the results of the first level wavelet decomposition of a sample image. The same operation as above is performed for the subsequent levels of decomposition with the lowest frequency sub-bands $D_j^0(m,n)$. Thus the generalized wavelet transform can be represented by $D_j^i(m,n), i = 0,1,..,3; j = 0,1,..\log_2^b - 1$, where ($b$ x b) is the block size, i is the sub-band and j is the scale index, respectively.

(a) (b)

Fig. 1: (a) Original Human_1 (bmp) image. (b) Wavelet sub-bands (LL, LH, HL, HH) representation after one level of decomposition.

In our study, we propose a block-based approach, where 8x8 overlapping blocks are used. We arranged the two level wavelet coefficients (smooth and details) corresponding to a block into a vector with row-wise ordering. The coefficient order during vector formation is as follows: $LL_2 \rightarrow HL_2 \rightarrow LH_2 \rightarrow HH_2 \rightarrow HL_1 \rightarrow LH_1 \rightarrow HH_1$.

2.2 Duplication detection algorithm

We have adopted a duplication detection algorithm similar to [3]. The various steps are as follows:

1. Let N be the total pixels in a grayscale image. Select sub-blocks at each pixel position and initialize the following parameters:
   b: number of pixels per sub-block. So there are a total of $N_b = (\sqrt{N} - \sqrt{b} + 1)^2$ sub-blocks.
   Q: number of quantization bins,
   N_n : number of neighboring rows to search in the lexicographically sorted matrix,
   N_f: minimum frequency threshold,
   N_d: minimum offset threshold.

2. Using wavelet decomposition, compute sub-band coefficients from each (b pixels) sub-block. We used two levels of decomposition for an 8 x 8 sub-block of image. This results in seven subbands per block.

3. Build an N_b x N_t matrix whose rows are given by the component-wise quantized coordinates, obtained by $\lfloor \vec{a}_i / Q \rfloor$, where $\bar{a}_i$ is the wavelet coefficients vector corresponding to i-th block. N_t is the dimension of row vector.

4. Sort the rows of the above matrix in lexicographic order to yield a matrix S. Let $\vec{s}_i$ denote the rows of S, and let (x_i, y_i) denote the position of the sub-blocks that corresponds to $\vec{s}_i$.

5. For every pair of rows $\vec{s}_i$ and $\vec{s}_j$ from S that $|i - j| < N_n$, place the pair of coordinates (x_i, y_i) and (x_j, y_j) onto a list.

6. For all elements in the list, compute their offsets, defined as:
   $$(x_i - x_j, y_i - y_j) \quad if \quad x_i - x_j > 0$$
   $$(x_j - x_i, y_i - y_j) \quad if \quad x_i - x_j < 0$$
   $$(0, |y_i - y_j|) \quad if \quad x_i = x_j.$$

7. Discard all pairs of coordinates with an offset frequency less than N_f.

8. Discard all pairs whose offset magnitude, $\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, is less than N_d.

9. Build a duplication map from the remaining pairs of blocks by assigning unique grayscale intensity values or colors to duplicated regions.

2.3 Semi-automatic detection of offset frequency threshold

A semi-automatic threshold technique is proposed to detect duplicated regions and to obtain refined results.

1. Sort offset frequencies N_f from low to high value. Select a threshold, Th=the highest N_f, say N_1
2. Obtain initial segmentation results by algorithm in 2.2.
3. Select a small sliding block (sb, 7 x 7) and count the number of labels at each location. Assign same label to the center pixel if (count >= (50% × #sb)); otherwise, assign 0.
4. Count final detection labels. If count >0, take next lower N_f (say Th=N_2) as threshold and continue from step 2; Stop when count=0. The final value for offset frequency is Th= N_1.

3. Experiments

3.1 Dataset

We used natural scene images in our duplication detection experiment. Set-1 consists of 20, while set-2 consists of 10 natural images. In set-2, five duplication sizes (24, 32, 48, 56, 64 pixels) per image constitutes a total 50 images. All are in BMP format having a size 256 x 256 taken by Digital camera. Tampered sets are made by copying and pasting region(s) of known and unknown shapes from the same images using programming.

3.2 Results

We performed an experiment on 20 tampered images by our algorithm. Some sample images and their duplication detection results are shown in figures 2, 3, 4, and 5.

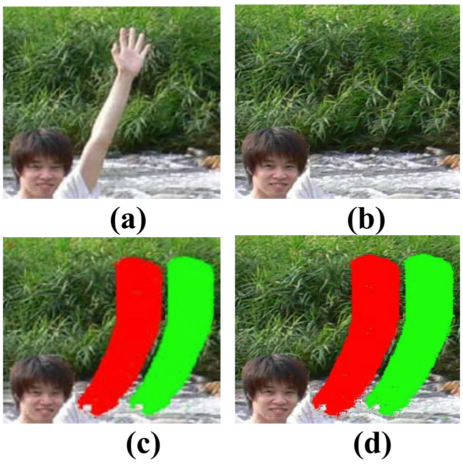


Fig. 2: Tampering detection results. (a) Original Human_1 (bmp) image, (b) Tampered image. Tampering detection results by (c) PCA based method (N_f =1200), and (d) Wavelet-based method (N_f =800).

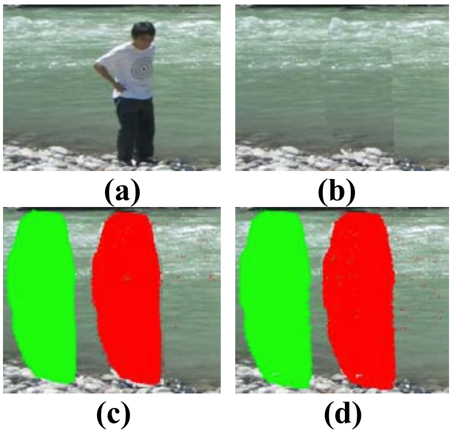


Fig. 3: Tampering detection results. (a) Original Human_2 (bmp) image, (b) Tampered image. Tampering detection results by (c) PCA based method (N_f =1200), and (d) Wavelet-based method (N_f =800).

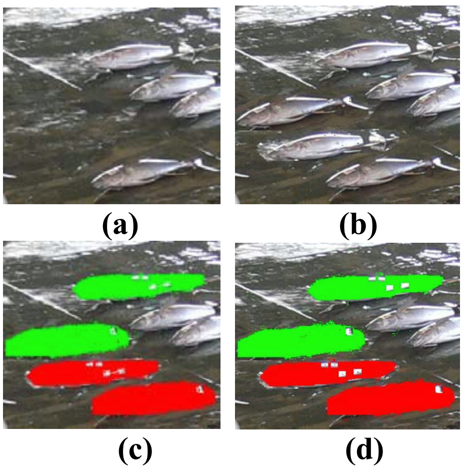


Fig. 4: Tampering detection results. (a) Original Fish_1 (bmp) image, (b) Tampered image (2 regions are copy-pasted). Tampering detection results by (c) PCA based method (N_f =1200), and (d) Wavelet-based method (N_f =800).

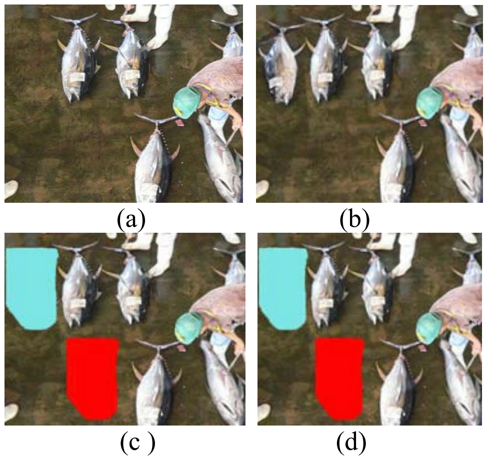
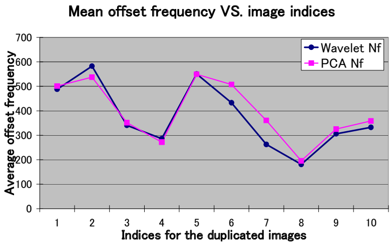


Fig. 5: Tampering detection results. (a) Original Fish_2 (bmp) image, (b) Tampered image (1 region are copy-pasted). Tampering detection results by (c) PCA based method (N_f =1200), and (d) Wavelet-based method (N_f =800).

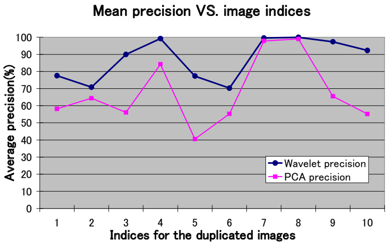
From the results, it is obvious that our proposed method can detect the duplicated regions well. The two colors in the above figures indicate copy and pasted regions. PCA based method can also detect the copy-pasted regions but it leads to lower precision and recall, to be shown later. Note that the following values were used for the parameters in our experiments. Q=256, N_n=50, N_d=16, b=N_t=64, N_f=800 (wavelet), and 1200 (PCA).

3.3 Performance analysis

We performed a second experiment for the quantitative analysis of the proposed methods. 10 natural (BMP format) images are duplicated by copying and pasting two regions in each image. Five square regions (24, 32, 48, 56, 64 pixels) are selected by programming in order to manipulate the original images. No post-processing is done on the duplicated images. Fig. 6 shows the average offset frequency, and corresponding precision plots over 10 images. Averaging is done on the mentioned five duplicated regions in each image. Figure indicates lower offset frequency (number of point-pairs) by wavelet-based method than that for the PCA-based. With higher precision, it also indicates the effectiveness of the proposed method for detecting relatively smaller duplicated regions. Fig.7 shows the average precision and recall plots against various duplicated regions. Averaging is done over 10 images for each duplicated region. Obviously the wavelet-based method achieves higher precision with the comparable recall rates compared to PCA based method. The overall average precision and recall rates are also shown in table 1.

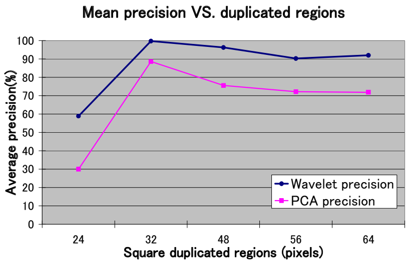


(a)

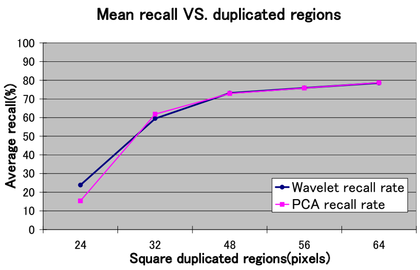


(b)

Fig. 6: Offset frequency and precision analysis. Average (a) offset frequency, and corresponding (b) precision plots for the wavelet and PCA based methods. Averaging is done for five different duplicated square regions (24, 32, 48, 56, and 64 pixels) in each image.



(a)



(b)

Fig. 7: Precision and recall analysis. Average (a) precision, and (b) recall plots against various duplicated square regions (24, 32, 48, 56, 64 pixels) for the wavelet and PCA based methods. Averaging is done over 10 images for each duplicated regions.

Table 1: Overall average precision and recall rates

Methods	Avg. Recall (%)	Avg. Precision (%)
PCA	60.9	67.6
Wavelet	62.1	87.4

4. Discussion

We have demonstrated the effectiveness of the proposed technique on digital forgeries of various complexities. Results show impressive performance in terms of duplication detection in natural images. Note that the precision and recall rates are computed by counting points in the copy or paste regions. The estimated sizes of the detected regions are less (by 7 pixels in four sides) than the actual copy-paste regions due to boundary effects in our block-based approach. Our iterative threshold detection scheme also refines the segmentation results by removing spurious, isolated points. However, we have yet to investigate the feature strength in the noisy environment or in the compressed domain. Since we have well-known algorithms for wavelet-based de-noising, we can take that advantage to deal with the noisy environment.

5. Conclusion

We presented an efficient and robust technique that automatically detects duplicated regions in an image. This technique adopts a special ordering of the wavelet coefficients from low to higher frequency subbands. Such ordering seems suitable to lexicographic sorting. Results show the effectiveness of this representation in the block matching process. However, we have yet to explore the feature strength in the noisy and compressed domains. It may be necessary to integrate various characteristics of multiple wavelets or other information for more robust feature representation.

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