Journal of Engineering and Applied Sciences 14 (20): 7679-7684, 2019
ISSN: 1816-949X

Image Splicing Detection using Uniform Local Binary Pattern and Wavelet Transform

[1]Eman I. Abd El-Latif, [2]Ahmed Taha and [2]Hala H. Zayed
[1]Department of Mathematics, Faculty of Science,
[2]Department of Computer Science, Faculty of Computers and Informatics,
Benha University, Benha, Egypt, eman.mohamed@fsc.bu.edu.eg

Abstract: Recently, the problem of detecting image splicing forgery attracts many researchers. Many algorithms have been presented to deal with this problem. However, most of them suffer from high dimensional feature vector. In this study, an algorithm is offered to reveal the splicing manipulation in the digital image with size feature vector. The proposed algorithm is predicated on Haar Wavelet Transform (HWT) and Uniform Local Binary Pattern (ULBP). The image color space is changed into YCbCr space. This algorithm works on the chrominance components and HWT is employed to get the four sub-bands. For every sub-band, ULBP is applied. The last feature vector is generated by merging features from the four sub-bands. Support Vector Machine (SVM) is used as a classifier. The proposed algorithm is examined on a freely accessible splicing image datasets (CASIA V1.0 and 2.0). The experiments prove that the proposed algorithm is successful for detecting the spliced image.

Key words: Splicing image forgery, tampered image detection, HWT, ULBP, SVM, experiments

INTRODUCTION

There are numerous human applications where images play an essential role such as courts, newspapers and websites. These applications can suffer from severe troubles, if the image content is manipulated. With the accessibility of the image modifying tools, it's simple to modify images (Julliand *et al*., 2015; Shih, 2012). Image forgery techniques alter or change a region in the original image to create another image, so that, it is difficult to be recognized as forged. To test the authentication of the image, numerous methodologies have been developed. These methodologies are classified into two types: active methodology (Potdar *et al*., 2005; Rey and Dugelay, 2002) and passive methodology (Qazi *et al*., 2013; Farid, 2009). The active methodology desires the digital watermarking or the signature to be added into the digital image throughout the imaging process. This is unwieldy for many of the cameras. Passive methodology does not want any data regarding the image, only the image itself. Splicing is one of the foremost common passive approaches (Burvin and Esther, 2014). Used to alter the image content. Splicing is performed by cutting a portion from one image and pasting it into another image.

Many algorithms have already been executed on image splicing. The existing algorithms are able to accomplish a good accuracy for detecting image splicing. However, it cannot be accomplishing a high accuracy with a comparatively little feature dimension. Many researches utilize the reduction-features algorithm to scale back the dimension of the features. However, it increases the computational complexity.

To tackle this problem, a passive algorithm is proposed to classify the image as original or tampered which can enhance the accuracy with comparatively low dimension feature vector. The proposed algorithm is predicated on Discrete Wavelet Transform (DWT) and Uniform Local Binary Pattern (ULBP). First, the image color space is changed over into the YCbCr. This color space is characterized by separating the Y luminance from the chrominance components (Cb and Cr) more effectively. In fact, the luminance is strong enough to hide the manipulation in images (Ibraheem *et al*., 2012). So, the proposed algorithm works on the extracted chrominance. DWT is then applied to the extracted chrominance to generate four sub-bands. ULBP is applied in the four sub-bands and then it combines features to generate the final feature vector. ULBP utilizes to scale back the number of the feature because it generates P(P-1)+3 patterns (where, p is the number of neighbors) (Saleh *et al*., 2013).

Literature review: Recently, several algorithms of passive image splicing detection are suggested. Numerous algorithms use Local Binary Pattern (LBP) for features extraction (Zhang *et al*., 2016; Alahmadi *et al*., 2017;

Corresponding Author: Eman I. Abd El-Latif, Department of Mathematics, Faculty of Science, Benha University, Benha, Egypt, eman.mohamed@fsc.bu.edu.eg

Hakimi *et al*., 2015; Muhammad *et al*., 2014; Kaur and Gupta, 2016). Yujin *et al*. present an algorithm for detecting image splicing dependent on Discrete Cosine Transform (DCT) and LBP. First, the color image is split into multi-size blocks. Then, DCT is applied to every block. Later, features are extracted using LBP. The last feature vector is created by concatenating different LBP histograms. Moreover, SVM is employed to classify input images by utilizing the dimensionality-reduced feature vectors.

An algorithm for detecting the manipulation in the image is recommended by Alahmadi *et al*. (2017). The algorithm is depended entirely on LBP and DCT. In the initial step, the chrominance component (Cb or Cr) is partitioned into blocks and then LBP and DCT are applied for every block. Additionally, the standard deviation is calculated within the second step. At last, the feature vectors are sent to SVM classifier to check the color image if it is original or tampered. The drawback of DCT is the blocking effect the relationship of the pixels within the one block is employed and the relationship between thepixels and the neighboring blocks is ignored.

By Hakimi *et al*. (2015), an algorithm dependent on Improved LBP (ILBP) and 2D DCT is presented. The chrominance component is splitted into blocks and ILBP is computed for each block. After ILBP, 2D DCT is applied and then standard division is computed. Finally, feature vectors are sent to k-Nearest Neighbors (KNN) for classification. However, kNN classifier has a few limitations. It computes the distance between the new object and all the training data. This can be rather slow, if there are a countless number of training data. Furthermore, KNN needs an outsized memory for storage.

Muhammad *et al*. (2014) use Steerable Pyramid Transform (SPT) and LBP to detect the image splicing. Within the first stage, the color image is changed to YcbCr chrominance space. Then SPT is applied to each chrominance component within the second stage. Features are taken out using LBP from every SPT sub-band. Different LBP histograms are converged to make the last features vector. Finally, SVM is applied within the last step to test the color image is spliced or not.

By Kaur and Gupta (2016), forgery detection algorithm dependent on Discrete Wavelet Transform (DWT) and LBP is suggested. The color image in the algorithm is changed into YCbCr color space. For Cr chrominance channel, DWT is utilized to obtain the low-level coefficients. Features are extracted from the four sub-bands (LL, LH, HL, HH) utilizing LBP. Histograms are concatenated from the four sub-bands to make the last feature vector. Then, SVM is employed for classification. The main restriction of this technique is that it uses a bigger number of features.

Hakimi and Mahdi (2015) suggest an algorithm dependent on LBP and DWT for detecting image manipulation. Firstly, LBP is applied in each bock of the chrominance component. Secondly, DWT is computed and then, the Principle Component Analysis (PCA) is utilized to diminish the dimension of the features. For classification, SVM is employed.

MATERIALS AND METHODS

The proposed algorithm: Figure 1 demonstrates the block diagram of the proposed algorithm to discover the manipulation within the image. Within the beginning, the image color space is changed into YCbCr space. In YCbCr, the Y is luminance part (brightness), Cb is the blue difference and Cr is the red difference. A study demonstrates that the human eyes are touchy to luminosity and luminosity is robust enough to cover the manipulation traces. Therefore, the proposed algorithm is

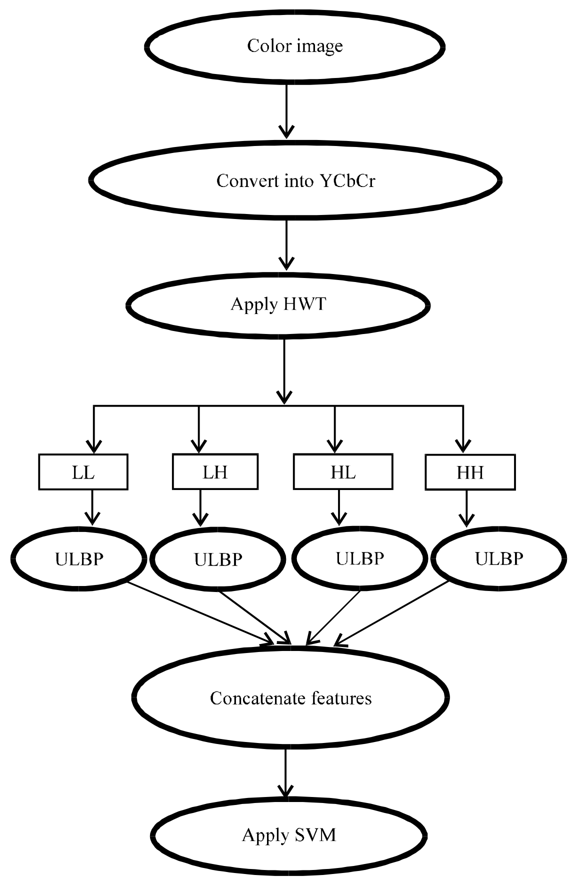

Fig. 1: Framework of the proposed algorithm

applied on the extracted components (Cb or Cr). Within the second step, HWT is applied to Cb. After applying HWT, the four sub-bands are extracted. The sub-bands are named as Low-Low (LL), High-Low (HL), Low-High (HL) and High-High (HH). The third step is to apply Uniform Local Binary Pattern (ULBP) into the four sub-bands. In the last step, the four feature vectors are concatenated and SVM is applied for the classifier.

Wavelet transforms: Wavelet transforms convert the image from the spatial domain to the frequency domain (Kingsbury and Magarey, 1998). There are different types of wavelet transforms but HWT is the simplest one. Also, it has efficient memory and fast (Porwik and Lisowska, 2004). HWT generates four sub-bands. They are labeled as LL, HL, LH and HH. Also, they know as a low-frequency part (LL) and the high-frequency parts (HL, LH and HH). The low-frequency components represent the base of an image and the high-frequency parts contain the information of edge in different directions. For example, if the sub-band image is generated using a high filter on the rows and a low filter on the columns, it is called the HL sub-band.

Uniform local binary pattern: LBP, the color image is changed into a gray image. Then, the central pixel value is taken as the threshold and it compares with its neighborhood values. The LBP process is calculated as (Huang *et al*., 2011):

$$LBP_{P,R} = \sum_{P=0}^{P-1} s(g_p - g_c)2^P \quad (1)$$

$$s(g_P - g_c) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (2)$$

The neighborhood pixels are represented by g_P and the center pixel is represented by g_c. P symbolizes the number of neighborhood pixels and r is the radius.

LBP has many disadvantages (Sree, 2015). LBP generates 2^P patterns and if p increases, the number of patterns also increases. For example, the eight neighboring pixels drive 256 patterns and if sixteen neighboring pixels drive 65, 536 patterns. The other drawback of the LBP is that it is sensitive to noise. A little change in the central pixel greatly changes in the LBP code as shown in Fig. 2. In LBP, many different structural patterns may have the same. LBP code as shown in Fig. 3.

Ojala *et al*. (2002) suggest the Uniform Local Binary Pattern (ULBP) to overcome the large dimension of LBP pattern. LBP is called ULBP if LBP includes 0-2 transitions from zero to one or from one to zero. Examples for ULBP are shown in Table 1. ULBP generates P (P-1)+3 patterns. For example, if p = 8 ULBP reduces its dimension from 2^8 = 256 to 59 gray values.

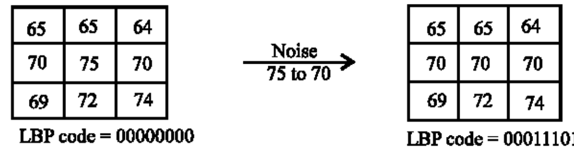

Fig. 2: The LBP with small noise

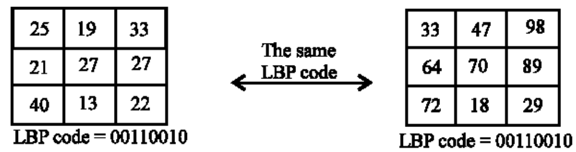

Fig. 3: The same LBP with different structure

Table 1: ULBP examples

ULBP code	No. of transition	Classification
00000000	Zero	ULBP
00000111	One	ULBP
11001001	Four	Not ULBP
01010010	Six	Not ULBP

Classification: There are a lot of different classifiers such as kNN (Bhatia, 2010), Naive Bayes (NB) classifier (Lakshmi and Kumari, 2018) and SVM (Ben-Hur and Weston, 2010), etc. kNN classifies the new object by calculating the distance between it and its neighbors. The new object is labeled to the class of its closest neighbor. The main drawbacks of the kNN are its large storage of data its expensive computations, its need to determine the number of nearest neighbors (k) and its slowness if there are a large number of data. NB classifier has a very strong assumption, it is difficult in large data, data is continuous and the features must be unrelated. However, in the proposed algorithm, SVM is utilized as a classifier. It gives a high accuracy, effective in high-dimensional data and flexibility to use a new kernel function (Ben-Hur and Weston, 2010).

RESULTS AND DISCUSSION

In order to measure the performance of the proposed algorithm, numerous experiments have been executed. In the first subsection, the description of the different datasets used is introduced. Evaluation metrics are illustrated in the next subsection. Lastly, the results of the experiments are studied and mentioned.

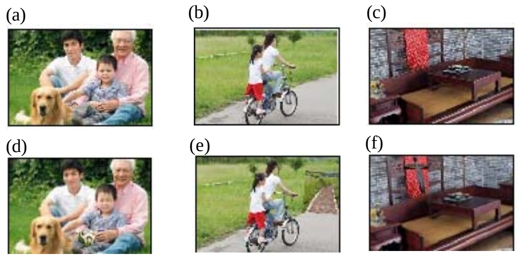

Fig. 4: Some example images in CASIA V1.0 dataset: a-c) Original and d-f) Spliced

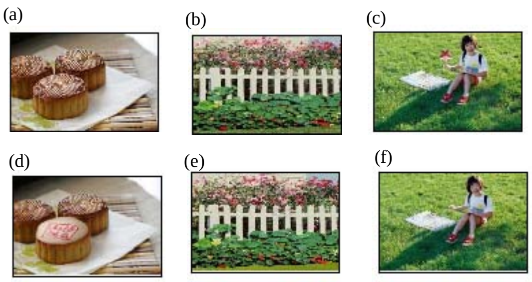

Fig. 5: Some example images in CASIA V2.0 dataset: a-c) Original and d-f) Spliced

Datasets description: In the literature, Columbia University provides two datasets for detecting splicing images: Columbia (compressed) and Columbia (uncompressed) (Ng *et al*., 2004). However, it provides only gray level images and the information of color images does not exist. This limits the use of such datasets with the color image based techniques. However, two public datasets are widely used to test such techniques: CASIA V1.0 and 2.0. Figure 4 and 5 show some example images of the two datasets. The top row is the original images and the next row is the spliced images. The aggregate number of images in CASIA V1.0 is 1,721 but in CASIA V2.0 is 12, 614. A detailed depiction of databases is presented in Table 2.

Evaluation metrics: In this subsection, accuracy, sensitivity, precision and F-measure are used to gauge the efficiency of the proposed algorithm (Zhang *et al*., 2016; Alahmadi *et al*., 2017; Hakimi *et al*., 2015; Muhammad *et al*., 2014; Kaur and Gupta, 2016). Accuracy is known as the percent proportion of images that are accurately classified and it is computed by the following Eq. 3:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP}\times 100 \quad (3)$$

where, True Positive (TP) is defined as the quantity of spliced images that are categorized as tampered. False Negative (FN) is the quantity of spliced images that are categorized as original image. True Negative (TN) is the quantity of original images that are categorized as original. False Positive (FP) is the quantity of original images that are categorized as tampered. Recall is the ratio of all positive cases that are accurately classified separated by all true positive cases. It is also known as True Positive Rate (TPR) and it is determined by the accompanying Eq. 4:

$$\text{Recall} = \frac{TP}{TP+FN}\times 100 \quad (4)$$

Precision is known as positive predictive value and it is computed using the following Eq. 5.

$$\text{Percision} = \frac{TP}{TP+FP}\times 100 \quad (5)$$

F-measure is the harmonic mean of precision and recall and it is computed as:

$$\text{F-Measures} = 2 * \frac{\text{Recall-Precision}}{\text{Recall+Orecision}} \quad (6)$$

Table 2: Overview of CASIA V1.0 and 2.0

Dataset	Image type	Image size	Authentic	Spliced
CASIA V1.0	jpg	384×256	800	921
CASIA V2.0	jpg tif bmp	240×160 to 900×600	7491	5123

Table 3: Evaluation metrics of the proposed algorithm

	Datasets	
Metrics	CASIA V1. (%)	CASIA V2. (%)
Accuracy	98.18	94.54
Precision	100.00	100.00
Recall	98.07	94.23
F-Measure	99.02	97.03

Table 3 displays the accuracy, precision, TPR and F-measure of various datasets for image splicing forgery detection. The accuracy of the algorithm is 98.18% in CASIA V1 and 94.54% in CASIA V2. Also, F-measure achieves 99.02 and 97.03% for CASIA V1 and 2, respectively.

Comparison with other passive algorithms: To assess the proposed algorithm, many comparisons using the same library (CASIA V1 and 2) are applied between the proposed algorithm and some of the other algorithms. Table 4 displays comparative experimental results of the proposed algorithm and five recent algorithms on CASIA V1.0: a Grey Level Run Length Matrix (GLRLM) (Mushtaq and Mir, 2014), deep learning (Zhang *et al*., 2016), Markov features, Markov features+QDCT (Li *et al*., 2017) and DWT+LBP (Muhammad *et al*., 2014).

Table 4: Experimental results of the proposed algorithm and other algorithms on CASIA V1.0

Methods	Accuracy (%)	Precision	Recall
Saleh *et al.* (2013)	94.19	N/A	N/A
Mushtaq and Mir (2014)	80.71	N/A	N/A
Kaur and Gupta (2016)	92.62	N/A	89.25%
Zhang *et al.* (2016)	87.51	59.43%	N/A
The proposed algorithm	98.18	100%	98.07%

Table 5: Experimental results of the proposed algorithm and other algorithms on CASIA V2.0

Methods	Accuracy (%)	Precision	Recall
He *et al.* (2012)	93.00	N/A	92.5%
Mushtaq and Mir (2014)	87.60	N/A	N/A
Li *et al.* (2017)	92.38	N/A	N/A
Kaur and Gupta (2016)	94.09	N/A	92%
Zhang *et al.* (2016)	81.91	80.65%	N/A
The proposed algorithm	94.54	100%	94.23%

Table 6: Comparisons of feature vector size in CASIA V1.0

Methods	Feature vector size	Accuracy (%)
Muhammad *et al.*(2014)	475	94.89
Li *et al.* (2017	588	95.48
Saleh *et al.*(2013)	972	95.96
The proposed algorithm	770	94.17
	236	98.18

Table 7: Comparisons of feature vector size in CASIA V2.0

Methods	Feature vector size	Accuracy (%)
Li *et al.* (2017)	588	92.00
	972	92.38
Kaur and Gupta (2016)	1.24	94.09
The proposed algorithm	236	94.54

In addition, the experimental results on CASIA V2.0 are displayed in Table 5. The proposed algorithm is better than the reported algorithm (Mushtaq and Mir, 2014) because it uses less number of hidden layers. The algorithm reported in is tested only in CASIA V2 and it is expensive for both the memory and the computing time. The limitation by Muhammad *et al.* (2014) is that its accuracy gets influenced when the area of the spliced image is little. Weber Local Descriptors (WLD0) by Saleh *et al.* (2013) is based on LBP for the orientation component. LBP has many disadvantages such as it is sensitive to the noise and the image rotation. Moreover, Table 6 and 7 show comparative results of the proposed algorithm with respect to the feature vector size and the accuracy achieved on both CASIA V1.0 and 2.0, respectively. It is noticed that, the proposed algorithm achieves comparative great accuracy with little features than the other algorithms. Furthermore, reducing the feature vector size of the proposed algorithm eliminates the time complexity. The features from the four sub-bands (LL, LH, HL and HH) in the proposed algorithm are concatenated to form the final feature vector of dimension.

CONCLUSION

In this study, a splicing image detection algorithm constructed totally on ULBP and HWT is proposed. First, the image is transformed into YCbCr color space. Second, HWT is applied to extract Chrominance components (Cb). Then, ULBP is applied to the four sub-bands and the results are combined to construct the feature vector, which is utilized as a contribution to the SVM. The trials are tested on two different databases (CASIA V1.0 and 2.0). The accuracy gives 98.18% for the first database and 94.54% for the second. The experiment effects confirm that the proposed algorithm not only works on the color image as well as realize high accuracy.

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