



Digital image splicing detection based on Markov features in DCT and DWT domain

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ABSTRACT

Image splicing is very common and fundamental in image tampering. To recover people's trust in digital images, the detection of image splicing is in great need. In this paper, a Markov based approach is proposed to detect this specific artifact. Firstly, the original Markov features generated from the transition probability matrices in DCT domain by Shi et al. is expanded to capture not only the intra-block but also the inter-block correlation between block DCT coefficients. Then, more features are constructed in DWT domain to characterize the three kinds of dependency among wavelet coefficients across positions, scales and orientations. After that, feature selection method SVM-RFE is used to fulfill the task of feature reduction, making the computational cost more manageable. Finally, support vector machine (SVM) is exploited to classify the authentic and spliced images using the final dimensionality-reduced feature vector. The experiment results demonstrate that the proposed approach can outperform some state-of-the-art methods.

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1. Introduction

Digital images have been widely used in our daily life. However, with the wide availability of sophisticated photo-editing softwares and the ease of distributing digital images (no matter authentic or forged) through the Internet, digital images no longer hold the unique stature as a definitive record of an event. With the aid of modern image processing techniques, different kinds of image forgeries could be easily created. Among all the possible image tampering operations, image splicing is the most common and fundamental one that creates a composite image by cutting and joining two or more photographs. Spliced images could hardly be perceived by the human visual system even without any post-processing. Therefore, developing some effective methods to detect digital image splicing is of great importance.

Existing technologies for digital image authentication can be roughly divided into two categories, referred to as active [1,2] and passive (blind) [3,4], respectively. Compared with the active methods, the passive (blind) ones can authenticate an image without any a priori knowledge, thus attracting more and more attentions recently.

The logic behind the passive (blind) detection is that, though visual clues are erasable, image tampering would inevitably alter the underlying statistical characteristic of an image. Based on this idea, lots of researches aiming at different kinds of image forgeries have been done. There are two common problems in image tampering, i.e. copy-move detection and image splicing detection. The primary mission of copy-move detection is to detect if there exists two or more similar regions in a single image, and to locate them if there is any [5,6]. Recently, the use of local visual features such as SIFT [7,8] for copy-move detection attracts much interest. Image splicing detection, on the contrary, aims at detecting if a given image is a composite one generated by cutting and joining two or more photographs. In this paper, we mainly focus on this subject, i.e. the detection of digital image splicing forgery. In the past, some blind detection approaches for image splicing forgery have been developed. In a series of papers [9–11], Ng et al. proposed to use a higher order moment spectra, bicoherence, as features for identifying spliced images. It is claimed that bicoherence is sensitive to quadratic phase coupling (QPC) caused by splicing discontinuity. The bicoherence based approach was tested on a well designed image data set [12], and a detection accuracy as high as 72% was reported. In [13], Fu et al. utilized Hilbert–Huang Transform (HHT) to capture the high non-linear and non-stationary nature introduced by image splicing. Besides, a statistical natural image model based on moments of characteristic function using wavelet decomposition was proposed in this work. By combining features extracted from these

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two methods, a detection accuracy of 80.15% was reported. In [14], geometry invariants and camera response function (CRF) were exploited by Hsu and Chang for image splicing detection in a semi-automatic manner. This work was extended to a fully automatic one by incorporating automatic image segmentation in [15]. In [16,17], the measure of local sharpness/blurriness was taken advantage of for splicing detection, which somewhat relied on whether the image under test had been smoothed/blurred or not. In [18], a tampered image detection scheme that could automatically locate the tampered region was proposed, but its application was restricted to JPEG images only. In [19], a Run-Length based scheme originally used in steganalysis was proposed to differentiate spliced images from authentic ones, and it was improved by He et al. in [20]. In [21], 2D phase congruency as well as statistical moments of wavelet characteristic function were proposed by Chen et al. as features to detect spliced images. They achieved a detection accuracy of 82.32% on Columbia Image Splicing Detection Evaluation Dataset [12] using SVM as the classifier. In [22], Shi et al. proposed a natural image model consisting of two kinds of statistical features. The model can achieve a detection accuracy of 91.87% on Columbia Image Splicing Detection Evaluation Dataset [12].

The approach proposed in [22] is very promising in terms of detection accuracy. One of the two kinds of statistical features is based on 1-D and 2-D moments of characteristic functions, which improves from a similar method already used in steganalysis [23]. The calculation of these moment based features is a little time-consuming. The other kind of features is based on Markov random process (Transition Probability Matrix) in DCT domain, which contributes most to the effectiveness and efficiency of the whole proposed approach. Inspired by the strong ability of Transition Probability Matrix in characterizing pixel/coefficient correlation, an expanded Markov based scheme in DCT and DWT domain is proposed for digital image splicing detection in this paper.

The rest of this paper is organized as follows. In Section 2, the proposed algorithm framework is presented first, then each part of it is described in detail. The experiment results of our proposed approach as well as the comparison with other schemes are shown in Section 3. Some issues in implementation are discussed in Section 4, and the conclusions are drawn in Section 5.

2. The proposed approach

In this section, the whole framework of the proposed approach is presented, followed by detailed description of each part.

2.1. Algorithm framework

The framework of the proposed Markov features based approach is shown in Fig. 1. Given a digital image, we not only extract Markov features in DCT (Discrete Cosine Transform) domain just like [22], but also in DWT (Discrete Wavelet Transform) domain. Note that, in contrast to [22], our approach focuses only on Markov features owing to their effectiveness and simplicity, dumping all the moment based features. Furthermore, when compared with the original DCT Markov features proposed in

[22], the Markov features extracted in DCT domain in our approach are expanded ones, for the purpose of capturing not only the intra-block correlation but also the inter-block correlation between DCT coefficients (similar concept was proposed in [24], the concrete implementation was not the same as ours though). Besides, due to DWT's desirable advantage of multi-resolution analysis, more Markov features are novelly constructed in DWT domain, with the aim of characterizing the residual correlation by modeling the three kinds of dependency among wavelet coefficients across positions, scales and orientations [25]. After all the related features are generated, a feature selection method referred as SVM-RFE (support vector machine recursive feature elimination) [26] is adopted to reduce the dimensionality of the final feature vector, making the computational complexity more manageable. Finally, the n -D feature vector obtained is used to distinguish authentic and spliced images with SVM as the classifier.

2.2. Expanded Markov features in DCT domain

The original Markov features in DCT domain proposed in [22] are very remarkable in capturing the differences between authentic and spliced images. They can be calculated following the six steps below.

Firstly, apply 8×8 block Discrete Cosine Transform on the source image pixel array, and the corresponding DCT coefficient array is obtained.

Secondly, round the DCT coefficients to integer and take absolute value (denote the obtained array as F).

Thirdly, calculate the horizontal and vertical difference arrays using

$$F_h(u, v) = F(u, v) - F(u + 1, v) \quad (1)$$

$$F_v(u, v) = F(u, v) - F(u, v + 1) \quad (2)$$

Fourthly, introduce a threshold T ($T \in N_+$), if the value of an element in F_h (or F_v) is either greater than T or smaller than $-T$, replace it with T or $-T$, respectively. Here, T is set to 4 (the same below), to reach a balance between detection performance and computational complexity.

Fifthly, calculate the horizontal and vertical transition probability matrices of F_h and F_v using

$$P1_h(i, j) = \frac{\sum_{u=1}^{S_u-2} \sum_{v=1}^{S_v} \delta(F_h(u, v) = i, F_h(u + 1, v) = j)}{\sum_{u=1}^{S_u-2} \sum_{v=1}^{S_v} \delta(F_h(u, v) = i)} \quad (3)$$

$$P1_v(i, j) = \frac{\sum_{u=1}^{S_u-1} \sum_{v=1}^{S_v-1} \delta(F_h(u, v) = i, F_h(u, v + 1) = j)}{\sum_{u=1}^{S_u-1} \sum_{v=1}^{S_v-1} \delta(F_h(u, v) = i)} \quad (4)$$

$$P2_h(i, j) = \frac{\sum_{u=1}^{S_u-1} \sum_{v=1}^{S_v-1} \delta(F_v(u, v) = i, F_v(u + 1, v) = j)}{\sum_{u=1}^{S_u-1} \sum_{v=1}^{S_v-1} \delta(F_v(u, v) = i)} \quad (5)$$

$$P2_v(i, j) = \frac{\sum_{u=1}^{S_u} \sum_{v=1}^{S_v-2} \delta(F_v(u, v) = i, F_v(u, v + 1) = j)}{\sum_{u=1}^{S_u} \sum_{v=1}^{S_v-2} \delta(F_v(u, v) = i)} \quad (6)$$

where $i, j \in \{-T, -T + 1, \dots, 0, \dots, T - 1, T\}$, S_u and S_v denote the dimensions of the original source image. $\delta(\cdot) = 1$ if and only if its arguments are satisfied, otherwise $\delta(\cdot) = 0$.

Finally, all the elements of all the transition probability matrices are used as features for image splicing detection. The dimensionality of the final feature vector is $(2T + 1) \times (2T + 1) \times 4$.

As suggested previously, though the original Markov features in DCT domain mentioned above excel in capturing intra-block correlation, the correlation caused by 8×8 blocking artifact is ignored. Here, we introduce some extra Markov features in DCT domain to represent the inter-block correlation between

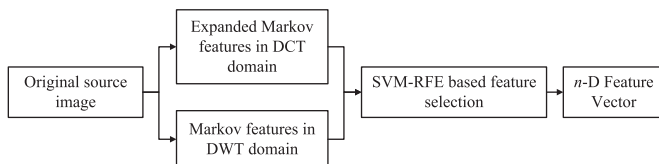


Fig. 1. The proposed algorithm framework.

corresponding coefficients. These extra Markov features can be calculated in a similar way as the original ones, as

$$G_h u, v = F u, v - F(u+8, v) \quad (7)$$

$$G_v(u, v) = F(u, v) - F(u, v+8) \quad (8)$$

$$P3_h(i, j) = \frac{\sum_{u=1}^{S_u-16} \sum_{v=1}^{S_v} \delta(G_h(u, v) = i, G_h(u+8, v) = j)}{\sum_{u=1}^{S_u-16} \sum_{v=1}^{S_v} \delta(G_h(u, v) = i)} \quad (9)$$

$$P3_v(i, j) = \frac{\sum_{u=1}^{S_u-8} \sum_{v=1}^{S_v-8} \delta(G_h(u, v) = i, G_h(u, v+8) = j)}{\sum_{u=1}^{S_u-8} \sum_{v=1}^{S_v-8} \delta(G_h(u, v) = i)} \quad (10)$$

$$P4_h(i, j) = \frac{\sum_{u=1}^{S_u-8} \sum_{v=1}^{S_v-8} \delta(G_v(u, v) = i, G_v(u+8, v) = j)}{\sum_{u=1}^{S_u-8} \sum_{v=1}^{S_v-8} \delta(G_v(u, v) = i)} \quad (11)$$

$$P4_v(i, j) = \frac{\sum_{u=1}^{S_u} \sum_{v=1}^{S_v-16} \delta(G_v(u, v) = i, G_v(u, v+8) = j)}{\sum_{u=1}^{S_u} \sum_{v=1}^{S_v-16} \delta(G_v(u, v) = i)} \quad (12)$$

where again $i, j \in \{-T, -T+1, \dots, 0, \dots, T-1, T\}$, thus producing $(2T+1) \times (2T+1) \times 4$ more Markov features. As a result, $(2T+1) \times (2T+1) \times 8$ Markov features in DCT domain in total are obtained.

2.3. Markov features in DWT domain

Wavelet analysis is good at catching the short-time transient or localized change in signals. Since the splicing boundaries are normally sharp transitions in nature, DWT is suitable for image splicing detection. Quite a few methods based on DWT have been proposed in the past, such as [21,27]. However, most of the methods deal with all the subbands independently after wavelet decomposition, neglecting the dependency among wavelet coefficients across positions, scales and orientations [25]. The approach proposed in [28] characterizes the three kinds of dependency among wavelet coefficients to some extent, but experiment results given by [10] demonstrate that it is not suitable for image splicing detection. Here, we resort to Markov random process (Transition Probability Matrix) to capture the aforementioned three kinds of dependency among wavelet coefficients, and make the acquired Markov features in DWT domain an important part in the whole image splicing detection scheme. The Markov features in DWT domain can be calculated as follows.

Firstly, apply 3-level Discrete Wavelet Transform on the source image pixel array, round all the coefficients of the 12 obtained subbands to the nearest integer and take absolute value. Denote the processed approximation subbands, horizontal detail subbands, vertical detail subbands and diagonal detail subbands as A_i, H_i, V_i, D_i ($i = 1, 2, 3$), respectively. Denote the source image pixel array as A_0 , and view it as a 0-th level approximation subband. Note that different wavelets perform differently, here we choose discrete Meyer wavelet because it is symmetrical and has characteristic of compact support in the frequency domain.

Secondly, consider one of the three kinds of dependency among wavelet coefficients: the dependency across positions. Using transition probability matrices to represent dependency among wavelet coefficients across positions are quite similar to characterize correlation between neighboring DCT coefficients. By replacing F in Eqs. (1) and (2) with each of the 13 wavelet subbands mentioned above, $13 \times 2 \times 2 = 52$ transition probability matrices and hence $(2T+1) \times (2T+1) \times 52$ Markov features can be obtained using Eqs. (3)–(6).

Thirdly, consider another dependency among wavelet coefficients: the dependency across scales. Take the horizontal

subbands H_i for an example, calculate a difference-like array using

$$H'_{i+1}(x, y) = \text{round} \left(\frac{H_i(2x-1, 2y-1) + H_i(2x-1, 2y) + H_i(2x, 2y-1) + H_i(2x, 2y)}{4} \right) - H_{i+1}(x, y) \quad (13)$$

where $i \in \{1, 2\}$. V'_{i+1} and D'_{i+1} can be calculated in a similar way. Based on these six difference-like arrays (i.e. $H'_2, H'_3, V'_2, V'_3, D'_2, D'_3$), $6 \times 2 = 12$ more transition probability matrices and hence $(2T+1) \times (2T+1) \times 12$ Markov features can be obtained.

Finally, consider the last dependency among wavelet coefficients: the dependency across orientations. First calculate cross-difference arrays using

$$HV_i(x, y) = H_i(x, y) - V_i(x, y) \quad (14)$$

$$VD_i(x, y) = V_i(x, y) - D_i(x, y) \quad (15)$$

$$DH_i(x, y) = D_i(x, y) - H_i(x, y) \quad (16)$$

where $i \in \{1, 2, 3\}$. Then $3 \times 3 \times 2 = 18$ more corresponding transition probability matrices and hence $(2T+1) \times (2T+1) \times 18$ Markov features can be obtained.

To sum up, $(2T+1) \times (2T+1) \times 82$ Markov features in DWT domain characterizing the three kinds of dependency among wavelet coefficients are obtained. These Markov features, along with the expanded ones in DCT domain mentioned in Section 2.2, comprise a natural image model which can be exploited to distinguish spliced images from authentic ones.

2.4. SVM-RFE based feature selection

Generally speaking, there are two main patterns when seeking appropriate features to classify authentic and spliced images. One is to find out the “exact” feature(s) which can theoretically be used to fulfill the task. However, as authentic and spliced images share a lot in common, finding out the “exact” features to differentiate them may not be easy, and what seemed to be perfectly right theoretically often turn out to be not so good (e.g. the approach we proposed in [20]). Another pattern is to first screen out some “coarse” features, and then pick the most useful ones out of them with the aid of certain feature selection methods, such as BFS (boosting feature selection) [29,30] and SVM-RFE (support vector machine recursive feature elimination) [26]. The approach proposed in this paper belongs to the second pattern, which can often achieve better detection performance, but at the cost of extra feature selection time.

The total number of the Markov features in the proposed natural image model is $(2T+1) \times (2T+1) \times 90$, that is 2250, 4410, 7290 if the threshold T is set to 2, 3, 4 respectively. To handle such a large number of developed features, it is unavoidable to use a feature selection method. Since the pattern classifier used in our experiments is SVM, here we choose SVM-RFE rather than BFS for the task of feature selection. SVM-RFE is an application of RFE using the weight magnitude as ranking criterion. Procedure of the algorithm in the linear case is shown in Algorithm 1 [26]. With the aid of Algorithm SVM-RFE, the dimensionality of the final feature vector could be reduced to n -D, where n is the set of different values, say 50, 100, 150, 200, to test its influence on the detection performance of the trained classifier.

Algorithm 1. SVM recursive feature elimination (SVM-RFE) algorithm.

- 1: **input**
Training examples: $\mathbf{X}_0 = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k, \dots, \mathbf{x}_\ell]^T$
Class labels: $\mathbf{y} = [y_1, y_2, \dots, y_k, \dots, y_\ell]^T$
- 2: Subset of surviving features: $\mathbf{s} = [1, 2, \dots, n]$
- 3: Feature ranked list: $r = []$

```

4: repeat
5:   Restrict training examples to good feature indices:
    $\mathbf{X} = \mathbf{X}_0(:, \mathbf{s})$ 
6:   Train the classifier:  $\alpha = \text{SVM\_train}(\mathbf{X}, \mathbf{y})$ 
7:   Compute the weight vector of dimension length( $\mathbf{s}$ ):
    $\mathbf{w} = \sum_k \alpha_k \mathbf{y}_k \mathbf{x}_k$ 
8:   Compute the ranking criteria:  $c_i = (\mathbf{w}_i)^2, \forall i$ 
9:   Find the feature with smallest ranking criterion:
    $f = \arg \min(\mathbf{c})$ 
10:  Update feature ranked list:  $\mathbf{r} = [\mathbf{s}(f), \mathbf{r}]$ 
11:  Eliminate the feature with smallest ranking criterion:
    $\mathbf{s} = \mathbf{s}(1 : f-1, f+1 : \text{length}(\mathbf{s}))$ 
12: until  $\mathbf{s} = []$ 
13: return Feature ranked list  $\mathbf{r}$ 

```

3. Experiments and results

In this section, we first introduce the experiment conditions, and then present a set of experiments to demonstrate the high performance and effectiveness of the proposed approach.

3.1. Experiment conditions

The public available and well recognized image dataset for splicing detection is the Columbia Image Splicing Detection Evaluation Dataset provided by DVMM, Columbia University [12]. It consists of 933 authentic and 912 spliced images with size of 128×128 pixels. The dataset is carefully designed for benchmarking the blind passive image splicing detection algorithms, so all the experiments presented in this paper are conducted on this specific dataset. Some example images of the dataset can be seen in Fig. 2, of which the first row are authentic images and the second row are spliced images. More details about the image dataset can be found in [12].

Support vector machine is utilized as the classifier in our experiments. Specifically, we choose the LIBSVM [31], and a RBF kernel is used. The optimal values for the parameter c and g are set through a “grid-search” method [32]. In the experiments, all the authentic images are labeled as $+1$ (positive), while all the

spliced images are labeled as -1 (negative). Then the classification of authentic and spliced images can be viewed as a binary decision problem, and the classifier LIBSVM is trained to solve it.

To evaluate the performance of the proposed approach, all the experiments and comparisons are tested on the above-mentioned dataset and the same classifier. The software platform is Matlab R2009b, and the hardware platform is a PC with a 2 G duo core processor. In each experiment, the average rate of 50 repeating independent tests is recorded. In each of the 50 runs, we randomly select 5/6 of the authentic images and 5/6 of the spliced images in the dataset to train the SVM classifier. Then the remaining 1/6 of the authentic and spliced images are used to test the trained classifier.

3.2. The detection performance of the proposed approach

Some common experiments are conducted first to assess the detection ability of the proposed approach. As mentioned above, the threshold T is set to 4, to reach a balance between detection performance and computational complexity. The dimensionality n of the reduced feature vector is set to different values, to evaluate its effect on the detection performance of the trained classifier. The detailed results are given in Table 1. Here, TP (true positive) rate is the ratio of correct classification of authentic images. TN (true negative) rate is the ratio of correct classification of spliced images. Accuracy is the weighted average value of TP rate and TN rate.

As shown in Table 1, when n is set to 100, the proposed approach can achieve a detection accuracy as high as 93.55%, which is very encouraging. When n is set to 150 or 200, a small drop in accuracy can be observed, it is probably due to the counteraction of some “unwanted” features. Removing “unwanted” features to boost detection accuracy is one of the reasons why we make use of SVM-RFE.

3.3. Comparison with other approaches

To evaluate the proposed approach comprehensively, we make a comparison between the proposed approach and some state-of-the-art image splicing detection methods. To ensure the validity



Fig. 2. Some example images of Columbia Image Splicing Detection Evaluation Dataset.

Table 1
Experiment results of the proposed approach with different feature dimensionality n ($T=4$).

Dimensionality n	TP (%)	TN (%)	Accuracy (%)
50	92.28	93.13	92.70
100	93.28	93.83	93.55
150	92.97	94.03	93.49
200	92.54	94.32	93.42

Table 2
Results on the comparison between the proposed approach and the other methods.

Feature vector	Dimensionality	Accuracy (%)
RLE [19]	61	76.52
PCCF [21]	120	82.32
NIM [22]	266	91.87
Our method	100	93.55

and fairness of the reported results of different methods, we conduct all the comparison experiments in the same experimental setup described in Section 3.1. The results of the experiments are shown in Table 2 (the feature vectors proposed in [22,21,19] are denoted as NIM, PCCF and RLE respectively), and the corresponding ROC curves are shown in Fig. 3.

It can be easily observed from Table 2 and Fig. 3 that our proposed approach performs the best out of the four presented splicing detection schemes. To our knowledge, the detection accuracy 93.55% achieved by our method is the highest one having been attained on the Columbia Image Splicing Detection Evaluation Dataset.

4. Some issues in implementation

In this section, some issues in implementation including the choice of threshold T , the contributions of different parts of the proposed natural image model and the choice of dataset are discussed.

4.1. Choice of threshold T

As mentioned above, the choice of threshold T directly determines the size of the transition probability matrices, and hence the dimensionality of the proposed feature vector before feature selection. Intuitively, if the value of T is too small, the correlation between DCT coefficients or the dependency among wavelet coefficients captured by the transition probability matrices might be insufficient to distinguish authentic and spliced images. If the value of T is too large, on the other hand, the computational cost might be unmanageable. Therefore, the choice of threshold T is a tradeoff between detection performance and computational complexity. Some experiments are conducted to assess the effect of choosing different T , and the experiment results are given in Table 3.

As shown in Table 3, when $T=4$, the proposed approach performs better than when $T=2$ or $T=3$, as is expected. However, we can also see that, compared with setting T to 4, setting T to 2 or 3 does not cause a dramatic drop in detection rates. Thus, if the computational cost is the main concern for some real applications, a threshold T of 2 or 3 might be more suitable.

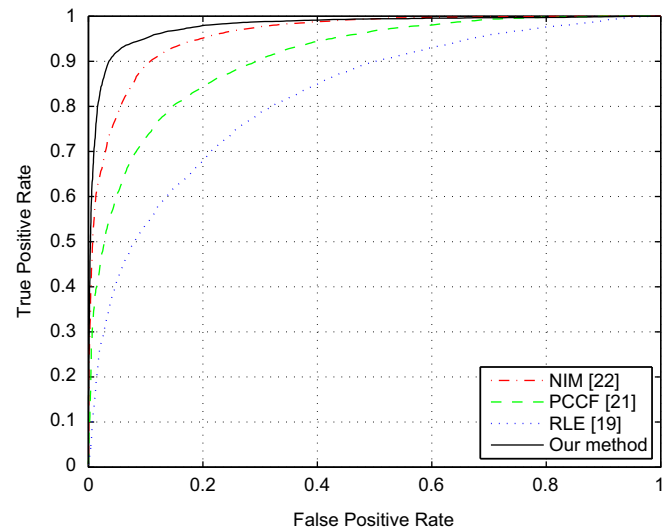


Fig. 3. The ROC curves of different feature vectors.

Table 3
Experiment results of the proposed approach with different threshold T .

Threshold T	Dimensionality n	TP (%)	TN (%)	Accuracy (%)
2	50	90.45	92.66	91.54
2	100	91.25	92.24	91.74
2	150	91.35	91.97	91.66
2	200	91.82	91.68	91.75
3	50	90.46	92.55	91.50
3	100	92.75	93.24	92.99
3	150	91.83	93.17	92.50
3	200	92.09	93.62	92.85
4	50	92.28	93.13	92.70
4	100	93.28	93.83	93.55
4	150	92.97	94.03	93.49
4	200	92.54	94.32	93.42

Table 4
Results on the detection rates of different parts of the proposed feature vector ($T=4$).

Markov features	Dimensionality n	TP (%)	TN (%)	Accuracy (%)
Expanded DCT	50	89.60	90.45	90.02
Expanded DCT	100	89.92	90.21	90.07
Expanded DCT	150	88.88	90.45	89.65
Expanded DCT	200	88.95	90.20	89.57
DWT	50	86.71	85.70	86.21
DWT	100	87.58	85.39	86.50
DWT	150	86.31	86.55	86.43
DWT	200	86.76	85.83	86.30
DCT + DWT	50	92.28	93.13	92.70
DCT + DWT	100	93.28	93.83	93.55
DCT + DWT	150	92.97	94.03	93.49
DCT + DWT	200	92.54	94.32	93.42

4.2. Contributions of different parts

Since the proposed natural image model consists of two different kinds of Markov features, i.e. expanded Markov features in DCT domain and Markov features in DWT domain, several experiments are further conducted to examine their respective contributions to the detection performance. The results are given in Table 4.

As shown in Table 4, the expanded Markov features in DCT domain perform a little better than the Markov features in DWT domain, this is probably due to DCT's superior ability in energy compaction, which results in more small coefficients in the corresponding difference arrays, and makes them more easily characterized by the bounded transition probability matrices. What is more, it can also be observed that, by combining these two kinds of Markov features, better detection performance can be achieved.

4.3. Choice of dataset

In Section 3, experiment results obtained on Columbia Image Splicing Detection Evaluation Dataset [12] were used to justify the effectiveness of the proposed approach. Though the dataset is popular, it is a little old and images (or image blocks) are at low resolution (128×128 pixels). As a consequence, one may question the validity of the final experiment results. In order to better demonstrate the potential of the proposed approach, extra experiments on some “real-world” images are conducted.

All the experiments are conducted under the same experiment conditions as described in Section 3.1, except that we use different dataset this time. The dataset we choose this time is CASIA Tampered Image Detection Evaluation Database V2.0 [33]. It consists of 7491 authentic and 5123 tampered color images with JPEG, BMP, or TIFF format. The images in this database are of different sizes, varying from 240×160 to 900×600 pixels. Some example images of the dataset can be seen in Fig. 4, of which the first row are authentic images and the second row are spliced images. It can be easily observed that images in this dataset are more realistic.

Experiment results obtained on CASIA Tampered Image Detection Evaluation Database V2.0 are shown in Table 5, and the corresponding ROC curves are given in Fig. 5. For comparison, we test the performance of the state-of-the-art method [22] on this dataset too. Again, all the comparison experiments are conducted in the same experimental setup described in Section 3.1 to ensure the credibility of the reported results.

As shown in Table 5 and Fig. 5, when tested on CASIA Tampered Image Detection Evaluation Database V2.0, our approach exceeds the state-of-the-art method [22] in detection accuracy by almost 5%. When compared with Table 2 and Fig. 3, the performance of both methods declines, which is quite what we expected because images in this new dataset are more realistic and hence more difficult to distinguish. Apart from

accuracy, we also calculate and record the computational cost of both methods, i.e. the total time to generate the final feature vector from one image in average. For the method proposed in [22], the total time equals to feature extraction time since it uses no feature selection method (such as SVM-RFE). For our method, however, the total time makes up of two parts, i.e. feature extraction time and feature selection time. As can be seen in Table 5, the computational cost (total time) of both methods is comparable and acceptable, which demonstrates that our method is more suitable for digital image splicing detection once the

Table 5

Experiment results obtained on CASIA Tampered Image Detection Evaluation Database V2.0.

Feature vector	NIM [22]	Our method
Dimensionality	266	100
Accuracy (%)	84.86	89.76
Feature extraction time (s)	4.479	2.218
Feature selection time (s)	0	2.158
Total time (s)	4.479	4.376

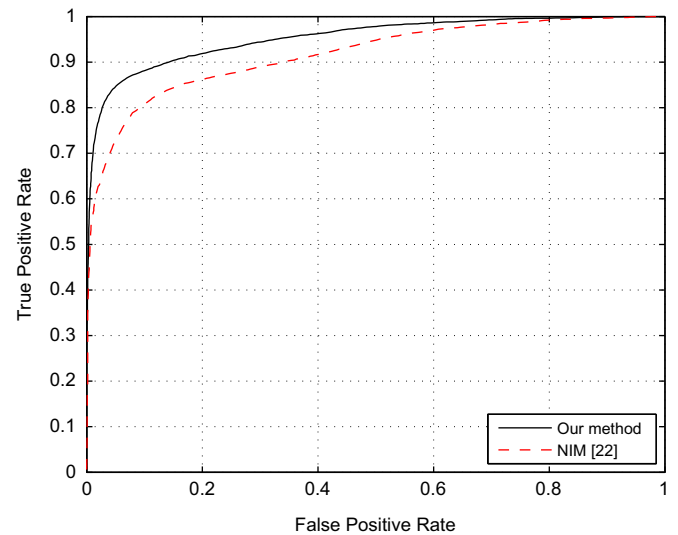


Fig. 5. The ROC curves obtained on CASIA Tampered Image Detection Evaluation Database V2.0.



Fig. 4. Some example images of CASIA Tampered Image Detection Evaluation Database V2.0.

detection accuracy and final feature vector dimensionality are all taken into consideration.

5. Conclusions

In this paper, a Markov based approach in DCT and DWT domain is proposed for image splicing detection. The proposed feature vector consists of two kinds of Markov features generated from the transition probability matrices, say the expanded Markov features in DCT domain and the Markov features in DWT domain. The former one is developed to capture the correlation between DCT coefficients, while the latter one is to characterize the dependency among wavelet coefficients across positions, scales and orientations. To handle a large number of developed features, feature selection method SVM-RFE is utilized. At last, the final dimensionality-reduced feature vector is used for image splicing detection with SVM as the classifier. Experiment results demonstrate that the proposed approach can outperform other state-of-the-art methods. Therefore, we believe our approach can be used in some areas of real applications.

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