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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.

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 asstatistical 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 simpleness, 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.

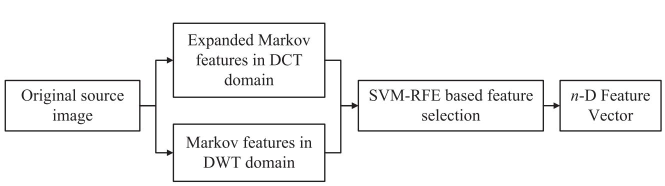

Fig. 1. The proposed algorithm framework.

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

$$F_h(u,v)=F(u,v)-F(u+1,v) \tag{1}$$

$$F_v(u,v)=F(u,v)-F(u,v+1) \tag{2}$$

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

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

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

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

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

where $i,j\in\{-T,-T+1,\ldots,0,\ldots,T-1,T\}$, 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 $(2T+1)\times(2T+1)\times4$.

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