

Inter-frame Video Forgery Detection Based on Block-Wise Brightness Variance Descriptor

Lu Zheng², Tanfeng Sun^{1,2(✉)}, and Yun-Qing Shi²

¹ School of Electronic Information and Electrical Engineering,
Shanghai Jiao Tong University, Shanghai, People's Republic of China
tfsun@sjtu.edu.cn

² Department of Electrical and Computer Engineering,
New Jersey Institute of Technology, Newark, NJ, USA

Abstract. Video forensics becomes more and more important than ever before. In this paper a new methodology based on Block-wise Brightness Variance Descriptor (BBVD) is proposed. It is capable of fast detecting video inter-frame forgery. Our proposed algorithm has been tested on a database consisting of 240 original and forged videos. The experiments have demonstrated that the precision rate is about 94.09 % in detecting the insertion forgery and the precision rate is 79.45 % in the forgery localization. Moreover, the time utilized for forgery detecting is shorter than the time used for video replay. On average the time of forgery detection is only about 73.4 % in video replay.

Keywords: Video forensics · Inter-frame forgery · Block-wise brightness variance descriptor

1 Introduction

Recently, due to availability of inexpensive and easily-operable multimedia tools, digital multimedia technology has experienced drastic advancements. At the same time, video forgery becomes much easier and it is more difficult to validate video content. Consequently, the origin and integrity of video can no longer be taken for granted. With these reasons, video forensics is becoming increasingly important, especially when the digital video content is used for legal support.

Currently, there are two types of forgery detection [1]: active detection (e.g., using watermark) and passive detection (e.g., blind detection). As for the active detection, the tampered region can be identified using a pre-embedded “semi”-fragile watermark in the video stream [2]. With the passive detection, also called blind detection, there is no need to embed any watermark into the protected files. On the contrary, the intrinsic features of the video itself can be used for forgery detection. As known, a digital video contains a large amount of information both in spatial domain and in temporal domain. Examples include, for examples, the correlation or similarity between neighboring frames.

Moreover, since the videos with watermarks embedded are sometimes can be considered as some kinds of forgery, the passive video forgery detection becomes more attractive and prevalent. In recent years, more and more approaches have been

developed for passive forgery video detection. There are three main categories for video forensic methods [3]. The first category is based on the video acquisition analysis, namely noise model or intrinsic parameters of CCD methods. One example in this regard is the methodology to use the non-uniformity of the dark current of CCD chips for camcorder identification proposed by Kurosawa et al. [4]. The second category is the detecting methods with video compression. For example, Tagliasacchi et al. [5] developed a method to detect block boundary for tampering trace by using estimation of the QP parameters. The last category is the video doctoring detection, including **copy-move detection in videos, which is based on inconsistencies in content, video editing and so on**. It was proposed to detect the copy-move operation in the video firstly by Wang and Farid [6]. They developed a method to detect frame duplication based on the correlation coefficient. The method based on inconsistencies in content is reported by Chao et al. [7]. They introduced an approach based on optical flow which is computed for each pixel to find out the discontinuity caused by inter-frame insertion or deletion during the forgery. It can detect frame insertion and deletion with high precision in large-scale testing. But it is so complicated that the computational expense is too much to meet the requirements of practical applications.

To sum up, there are only a small number of algorithms to detect video inter-frame forgery. In this paper, a novel algorithm which is block-wise based using the brightness variance descriptor is proposed. It is highly efficient because of the algorithm's low computational complexity. The remaining paper is divided into four sections. Section 2 is about feature extraction. The propose scheme is presented in Sect. 3. Section 4 contains experiment results and discussion. The conclusion is drawn in Sect. 5.

2 Feature Extraction

In this paper, a new feature, called the block-wise brightness variance descriptor (BBVD) in consistent video sequence, is proposed for video inter-frame forgery detection. The main idea is that the consistency of the ratio of the BBVD in equal time intervals will be disturbed in frame forgery videos. This method can not only detect whether the video is tampered or not, but also detect the location of the frame forgery.

2.1 Base of the Proposed New Features

As is known, digital video not only contains a large amount of information in the spatial domain, but also in the temporal domain. In the temporal domain, the correlation of adjacent frames is very high, which means the corresponding variation is relatively rather low. So if some frames are inserted or deleted to tamper the original content of the original videos, the variance of brightness should often be changed largely.

A new idea can be obtained according to Weber's Law [8], which describes the perceptual difference between the increment stimulus and the original stimulus. The ratio of the variation can be defined as the follows:

$$R = \frac{\Delta B}{B} \quad (1)$$

where B is the brightness or the gray value of a pixel in one frame and ΔB is the variant value from different pixels, R is the ratio of the variation of the brightness versus original brightness. The R is a constant in the equation.

So a constant or slow variable of brightness ratio should be obtained from consecutive frames in the video frames sequence.

Moreover, due to the persistence phenomenon of human vision [9], the image can be retained in the human visual system for about 0.1 to 0.4 s after its disappearance. So, in order to guarantee the consistency of the video content, any two frames with some short time intervals such as 0.4 s must have only small variation. As for the common video frame rate, i.e. 24 frames per second, the minimum value of time interval is as follows:

$$24 \text{ fps} \times 0.4 \text{ s} = 9.6 \text{ frame} \approx 10 \text{ frame} \quad (2)$$

that means every two frames with an interval within approximately 10 frames still have a correlation to some degree.

Here a constant or slow variable of brightness ratio should be kept from non-consecutive but rather adjacent frames, such as 10-frames interval in the video frames sequence, i.e.,

$$R_{BVD} = \frac{\Delta B_f}{B_f} \quad (3)$$

where B_f is the brightness or gray value of the first frame and ΔB_f is the difference of first frame versus its adjacent 10th frame. R_{BVD} is the ratio the difference of two frames versus first frame. For an original video, the ratio between the two frames with a certain time interval is usually a constant or tardily variable. However, this consistency will be disturbed in the inter-frame forgery video. The feature used in the paper is based on the R_{BVD} .

2.2 Sub-sequences Group Generation

Before feature extraction, the whole video sequence needs to be partitioned into several short temporal sub-sequences with a same duration. In this experiment, the full-length video sequence is partitioned into a series of short overlapping sub-sequences groups, i.e. $G = \{g_1, g_2, g_3 \dots g_j \dots g_n\}$, where n is the total number of the sub-sequence group. The length of the each sub-sequence is 15 frames with 5 frames overlapping to satisfy the persistence phenomenon of vision for human eye [9], that is,

- (1) 1st sub-sequence group: 1st frame to 15th frame;
- (2) 2nd sub-sequence group: 11th frame to 25th frame
- (3) 3rd sub-sequence group: 21st frame to 35th frame

.....

(j) j^{th} sub-sequence group: w^{th} frame to $(w + 15)^{\text{th}}$ frame, where $w = [(j-1) \times 10 + 1]$.

Short-temporal video sequences analysis, rather than frame by frame analysis, is performed to accelerate forgery detection.

2.3 Feature Model Based on Sub-block

In the paper, the new feature, R_{BVD} , calculated from each so called sub-sequence group $\{g_n\}$ is used to determine whether a test video has been tampered or not. In order to reduce the negative influence of the mutation or fluctuation in some part of the frame, each frame is partitioned into a series of 16 (4×4) sub-blocks, denoted as $B_{\text{block}} = \{b_1, b_2, b_3, \dots, b_{16}\}$. For each sub-sequence group, taking the j^{th} sub-sequence group as an example, obtained the first frame (w^{th} frame) and the last frame ($(w + 15)^{\text{th}}$ frame) in the current sub-sequence group. According to Eq. (3), compute R_{BBVD} between each sub-block in the first frame and the corresponding sub-block in the last frame in each sub-sequence group. Then calculated the average value of the all the ratio of BBVD in the current sub-sequence.

$$R_{BBVD} = \frac{\Delta B_{\text{block}}}{B_{\text{ave}}} = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N \frac{Bf_{ij} - Bl_{ij}}{B_{\text{ave}}} \quad (4)$$

where, R_{BBVD} represents the ratio of BBVD between the each block in the first frame and the corresponding block in the last frame in each sub-sequence group. ΔB_{block} is defined as the variation of the gray value of pixels in the corresponding sub-blocks. Bf_{ij} and Bl_{ij} represent the gray value in each pixel of the current block in the first frame and the last frame of the current sub-sequence group respectively. M and N represent the number of the pixel in row and column in each block. B_{ave} is the average gray value of pixels in the current block of the first frame in each sub-sequence group and B_{ave} can be defined as follows:

$$B_{\text{ave}} = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N Bf_{ij} \quad (5)$$

As the R_{BBVD} of each block in the corresponding two frames has been calculated in each group, calculate the average of these series R_{BVD} , value defined as R_{BVD} , in each sub-sequence.

$$R_{BVD} = \frac{1}{16} \sum_{i=1}^{16} R_{bi} \quad (6)$$

R_{BVD} is our new feature for detecting video inter-frame forgery. R_{bi} is an element value of a 8×8 block. The process of algorithm is introduced in the following section.

3 Proposed Scheme

The new feature is proposed in the previous section. In this section, we describe the proposed scheme.

3.1 Assumptions Made for the Proposed Scheme

As mentioned above, human eyes can not perceive video content modification if only very few frames have been modified. In this paper, only the meaningful video frame insertion is concerned, by meaningful, it means the forgery content can be perceived by human eye. Thus, it is based on several assumptions as listed below:

1. Each test video sequence is one shot video sequence taken by the stationary video camera.
2. Each forged video has only one of the following two type of forgery: frame insertion or frame deletion.
3. In frame insertion or frame deletion, the number of the inserted or deleted frame is more than 10.
4. Each frame insertion or deletion video only has been performed once.

3.2 Framework

In Fig. 1, the proposed framework is presented. The main process of forgery detection includes short-temporal frame sequence partitioning, sub-block division in each frame, R_{BVD} obtained extraction, adaptive self-threshold selection, fast detection, forgery type detection and forgery localization. The detailed process will be described in the following subsections.

3.3 Feature Extraction

The detailed steps of feature extraction are given as follows:

1. Given a test video, parse it into a series of frames.
2. Partition the full-length video sequence into short overlapping sub-sequence groups as we discussed before, i.e. $G = \{g_1, g_2, g_3 \dots g_j \dots g_n\}$. Note that there is some frames overlap between consecutive groups.
3. For each frame, partition it into 4×4 blocks, denoted as $B = \{b_1, b_2, b_3 \dots b_i \dots b_{16}\}$.
4. By using Eq. (4), calculate the ratio of BBVD for each group.
5. By utilizing Eqs. (5) and (6), the average value of ratio of BBVD, denoted as R_{BVD} , is calculated.

In this way, a series of R_{BVD} is calculated in the whole-length video sequence as the shown in Fig. 1. Among a series value of R_{BVD} , there are two obvious peak points. As mentioned before, the ratio of BBVD is close to a constant in a normal video and this consistency will be disturbed in the frame insertion video. As shown in Fig. 1,

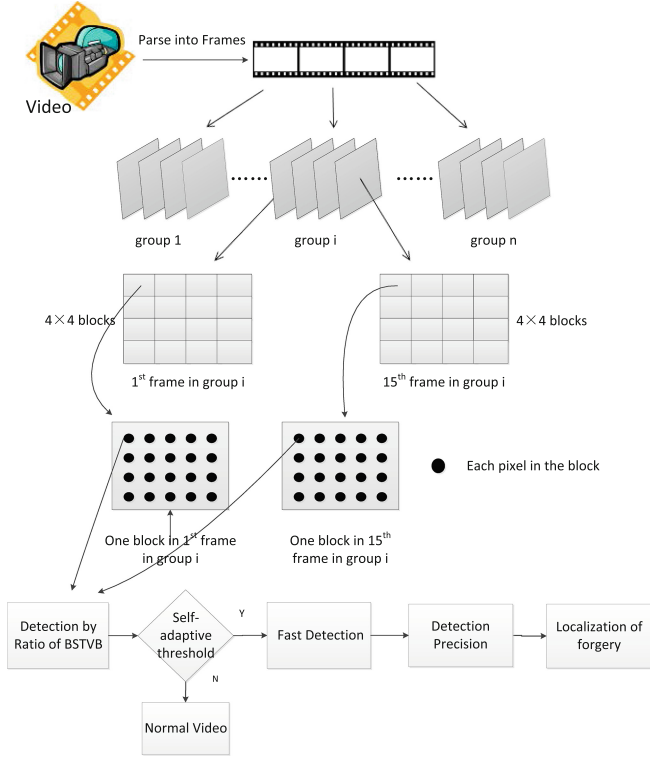


Fig. 1. Framework of proposed scheme

the corresponding sub-sequences to these two peak points must contain the original frame and the insertion frame. Although it is easy to determine the peak point from the figure, how to get a self-adaptive threshold is important.

3.4 Self-adaptive Threshold Selection Method

The so-called 3σ Rule is the common criteria of gross error detection in the probability theory. Its basic assumption is that the random error obey the normal distribution, and then the absolute value of error mainly concentrated in the vicinity of the its mean. It can be expressed as follows:

$$P(-3\sigma < z - \mu < 3\sigma) = 0.9974 \quad (7)$$

where $z \sim N(\mu, \sigma^2)$, σ is the standard deviation of z . Equation (7) implies that data can be treated as the gross error is more than 3σ .

When applying the 3σ Rule to our method, if the ratio of BBVD is more than 3σ , where σ refers to the standard deviation of a sequence of ratio of BBVD derived from every two frames with the equal time interval in a video, this value can be treated as the

gross error. That means these two frames are no longer subordinated to consistency of those frames with equal time intervals, which indicating the existence of the insertion frames. In this way, the approximate location of the insertion frame will be found.

As mentioned above, whether R_{BBVD} is subordinated to the Gaussian distribution needs to be justified before applying the 3σ Rule to our method. The verified results are given in Fig. 2.

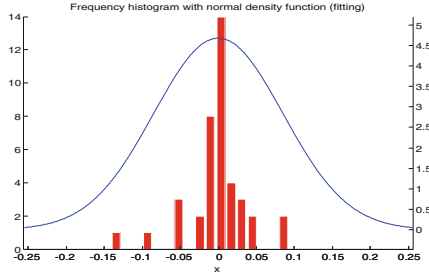


Fig. 2. The curve-fitting of frequency histogram conform to Gaussian distribution of R_{BBVD} .

From Fig. 2, it is obvious that the series of R_{BBVD} , is subordinated to Gaussian distribution and thus the 3σ Rule can be applied to the BBVD sequence. Since most R_{BBVD} , are close to 0, only few values have large numerical deviation which can be treated as the gross error. Usually, the gross error implies that the corresponding sub-sequence frames contain either inserted frames or deleted frames.

After validation, we can calculate the standard deviation of the series of R_{BVD} , i.e., $\{R_{BVD1}, R_{BVD2}, R_{BVD3}, \dots, R_{BVDn}\}$ in the in the whole-length video sequence as follows.

$$\mu_{BVD} = \frac{1}{N} \sum_{i=1}^N R_{BVDi} \quad (8)$$

$$\sigma_{BVD} = \sqrt{\frac{1}{N} \sum_{i=1}^n (R_{BVDi} - \mu)^2} \quad (9)$$

where μ_{BVD} is the mean value of the R_{BVD} , σ_{BVD} is the standard deviation of series R_{BVD} . So we can obtain the self-adaptive threshold from the testing video frame sequence.

3.5 Inter-frame Forgery Type Detection

The details of the inter-frame forgery detection is as follows:

1. According to the 3σ Rule, if the value of R_{BVD} is more than 3σ , this value can be treated as a gross error.
2. If none of R_{BVD} is more than 3σ , the test video is determined as a normal video.

3. If the number of the gross error is one peak, the test video is frame deletion video.
4. If the number of the gross error is more than two, the test video is a frame insertion video.

As for the frame insertion video, the ratio of BBVD at the beginning and the end of the insertion frame has a greater volatility than other normal frames. As shown in Fig. 3, two distinct peak points occur in the whole series of R_{BVD} . Thus, it is easy to conclude that the corresponding sub-sequence group of these two peak points must contain the insertion frame and original frame. Some videos have abrupt change to result in false detection will be analyzed in the experiment. As for the deletion video, only just one peak point can be found if only one deleting operation was done. Furthermore, the peak value of the deletion usually is less than that of the insertion.

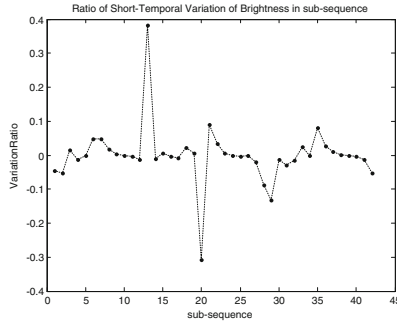


Fig. 3. The sampling of the ratio of BBVD with frame insertion forgery in each sub-sequence

3.6 Forgery Localization

The process of the insertion forgery localization is the same as the deletion forgery localization. So the forgery localization of the insertion detection was given as an explanation. Since two maximum peak points have been found, it is easy to figure out the corresponding sub-sequences. Each sub-sequence has 15 frames, which contains the normal frames and insertion frames. To specify the accurate location of the frame insertion, the ratio of BBVD for frame to frame needs to be calculated further.

The details of the insertion forgery localization is as follows:

Step 1. Select the first frame, i.e., f_i , as a reference position in the sub-sequence which includes the peak point.

Step 2. Select 40 adjacent frames of which 20 frames are ahead of f_i and the other 20 frames are behind.

Step 3. Calculate the ration of BBVD of each two adjacent frames by utilizing Eqs. (4) and (5). In this way, two new series of ratio of BBVD frame by frame can be calculated, each of which is corresponding to a peak point. The results are shown in Fig. 4.

The variation between two adjacent frames in non-tampered frame sequence is extremely low which implies that the ratio of BBVD is close to 0. Only two corresponding

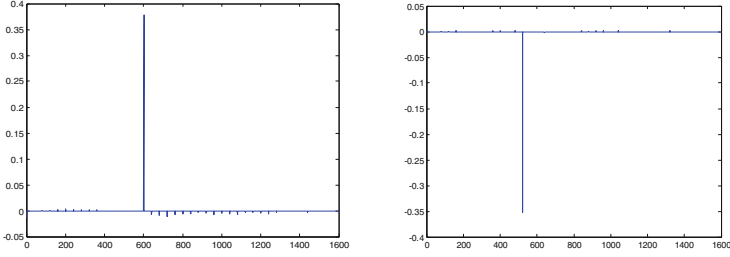


Fig. 4. Results of the ratio of BBVD calculated by frame to frame

frames are from different video frame subsequences can lead to a sudden volatility. As shown in Fig. 4, all the values except one point are nearly equal to 0 in each figure. Those points of which values equal to 0 mean that the corresponding two frames are the continuous and original frame sequence. And the point with a sudden volatility means the corresponding frames contain the original frame and insertion frame. Thus, select the maximum value of each result and find the corresponding frames to this result. The localization of frame is the accurate location of the frame insertion. The deletion detection is the same process as the insertion detection.

4 Experimental Results and Discussion

The scheme of the inter-frame video forgery detection has been presented above. Here experimental works are presented to verify that our algorithm is feasible and has good performance.

4.1 Video Database

The original videos are from the Recognition of Human Actions Database [9]. The video database contains six types of human actions (walking, jogging, running, boxing, hand waving and hand clapping) in four different scenarios: outdoors s1, outdoors with scale variation s2, outdoors with different clothes s3, and indoors s4, as illustrated below.

All sequences were taken over homogeneous backgrounds with a static camera with 25 fps frame rate. The format of all the video sequence is AVI file format [9].

The insertion forgery database used in our work follows Chao et al. [7] scheme for fair comparison. The test video database is generated with TRECVID Content Based Copy Detection (CBCD) scripts. The CBCD scripts can generate frame insertion videos automatically with random length. In our approach, 220 frame insertion video sequences and 20 normal video sequences are selected for testing. Each frame is of 240×320 pixels in size and the length of each video sequence is ranged from 375 frames to 625 frames (approximately 15 to 25 s).

4.2 Evaluation Parameter

To evaluate the detection efficiency, two criterions called the recall rate, R_r , and the precision rate, R_p , are used. The recall rate is the proportion of correctly detected videos among all tampered videos. The precision rate refers to the percentage of correctly detected video among all the detected videos. The recall rate, R_r , and the precision rate, R_p , are defined as follows:

$$R_r = \frac{N_c}{N_c + N_m} \times 100 \% \quad (10)$$

$$R_p = \frac{N_c}{N_c + N_f} \times 100 \% \quad (11)$$

where N_c is the number of correctly detected video forgeries; N_m is the number of missed video forgeries; N_f is the number of falsely detected video forgeries.

4.3 Experiments on Frame Insertion Detection

Video Frame Insertion Detection. As for validation of the video frame insertion, the recall rate reaches 98.67 % and the precision rate reaches 94.09 % as shown in Table 1.

Table 1. Test results for validation of video frame insertion

	N_c	N_m	N_f	R_r (%)	R_p (%)
Our scheme	223	3	14	98.67	94.09
Chao scheme [7]	2863	137	140	95.43	95.34

From Table 1, we can conclude: Our scheme has a higher recall rate than that achieved by Chao scheme [7], but a lower precision rate to some extent. That is our scheme pay more attention to efficiency than to precision.

Above comparison is not peer to peer, because the Chao [7] is using more than 3000 forgery video sequence, but only 220 forgery video sequences are used in our scheme. So we just perform qualitative analysis.

Video Frame Insertion Localization. For the localization of frame insertion, the recall rate reaches 89.23 % and the precision rate reaches 79.45 %.

Since the localization of frame insertion detection is not discussed in Chao [7], the localization performance is not compared between the two schemes. From Table 1, we can conclude that the proposed scheme can detect most localizations of insertion forgery. From the above data, there are some deviation in frame insertion localization. Because there are some constraints on the test videos which are based on the several assumptions mentioned before, this algorithm has susceptibility to some extent. That is, if the object moves too fast, some values of R_{BBVD} will has a bigger and abrupt variation, which is not caused by the frame insertion.

4.4 Real-Time Applications

There are 10 video sequences with different lengths and sizes used in experiment and shown in Table 2. Table 2 describes the relationship between the tested video length and the test duration (namely computational cost). For a video of 2.85 MB lasting 45 s long, it takes about 8.4 s to detect the frame insertion. The time-cost of our scheme is shown in Table 2. There is no time cost discussed in Chao [7], however the processing time of their scheme is usually longer than the video length because of its complexity of pixel-based optical flow calculation.

Table 2. Time-cost of computing in our scheme among different length videos^a

Number	Video length (s)	Video size (MB)	Average time-cost (s)	Ratio of real-time (%)
1	45	2.85	8.4	0.19
2	35	2.15	7.4	0.21
3	31	1.93	7.1	0.23
4	27	1.68	6.7	0.25
5	26	1.67	7.3	0.28
6	21	1.39	6.2	0.30
7	20	1.24	5.7	0.29
8	19	1.18	4.6	0.24
9	17	0.75	5.6	0.33
10	16	1.00	5.5	0.34

^awith CPU i7-2820, 4 GB RAM, Win7 64bit, and Matlab2012b.

Form Table 2, we can conclude that the gross trend of time-cost of our scheme is directly in proportion to the video length. It is 73.4 % short than video length on average. There are some exceptional cases, such as number 4 and 5 in Table 2. As a result, our scheme can satisfy real-time request in most applications.

4.5 Frame Insertion with Different Insertion Number

Two hundred forgery video sequences are generated with TRECVID Content Based Copy Detection (CBCD) scripts and are selected to test the detection efficiency with different frame insertion numbers. Those video sequences can be classified into two groups. The 100 video sequences are those with less than 25-frame insertion and the other 100 video sequences are those with more than 25-frame insertion.

According to the results listed in Table 3, we can conclude as follows. In term of detection precision, R_p , our scheme is 11.6 % lower than that achieved by Chao [7]. In term of detection recall, our scheme is compatible to than achieved by Chao [7]. The proposed approach is more efficient than Chao [7] in real-time applications. Moreover, it is obvious that both recall rate and precision rate will drop down with fewer frames insertion. Frame insertion forgery with more than 25-frame insertion will lead to a higher detection accuracy. It is in accord with Chao's conclusion.

Table 3. Test results with different frame insertion numbers

	Insertion frames	$N_c + N_m + N_f$	N_c	N_m	N_f	R_r (%)	R_p (%)
Our scheme	$N \leq 25$	100	66	13	21	83.5	75.8
	$N > 25$	100	82	5	13	94.25	86.32
Chao scheme[7]	$N = 25$	608	566	44	8	92.67	95.58
	$N = 100$	612	566	34	12	94.33	97.92

5 Conclusion

In this paper, a novel feature, called block-wise brightness variance descriptor (BBVD), is proposed. And a fast scheme for video frame forgery detection based on the new feature is developed. Experiments have shown that the recall rate in detecting video frame insertion reaches 98.67 % and the precision rate reaches 94.09 % as shown in Table 1. As for the detecting the location of the frame insertion, the recall rate reaches 89.23 % and the precision rate reaches 79.45 %. It is more suitable for real-time processing than Chao et al.'s scheme [7].

Future work will focus on improving the robustness when detecting the location of video frame insertion and enhancing its recall rate and precision rate.

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