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Video Inter-frame Forgery Identification Based on Optical Flow Consistency

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Abstract: Identifying inter-frame forgery is a hot topic in video forensics. In this paper, we propose a method based on the assumption that the optical flows are consistent in an original video, while in forgeries the consistency will be destroyed. We first extract optical flow from frames of videos and then calculate the optical flow consistency after normalization and quantization as distinguishing feature to identify inter-frame forgeries. We train the Support Vector Machine to classify original videos and video forgeries with optical flow consistency feature of some sample videos and test the classification accuracy in a large database. Experimental results show that the proposed method is efficient in classifying original videos and forgeries. Furthermore, the proposed method performs also pretty well in classifying frame insertion and frame deletion forgeries. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Inter-frame forgeries, Frame insertion, Frame deletion, Optical flow consistency, Video forensics, Classification.

1. Introduction

Nowadays with the ongoing development of video editing techniques, it becomes increasingly easy to modify the digital videos. How to identify the authenticity of videos has become an important field in information security.

Video forensics aims to look for features that can distinguish video forgeries from original videos, thus people can identify the authenticity of a given video. A kind of distinguishing method which is based on video content and composed of copy-move detection and inter-frame tampering detection becomes a hot topic in video forensics. Chih-Chung *et al.* [1] used correlation of noise residue to locate forged regions in a video. Leida *et al.* [2] presented a method to detect the removed object in video by employing the magnitude and orientation of motion vectors. A.V. *et al.* [3] detected the spatial and temporal copy-paste tampering based on Histogram of Oriented Gradients (HOG) feature matching and video compression properties. For inter-frame forgeries, such as frame insertion and frame deletion forgeries, some effective methods were proposed [4, 5]. Juan *et al.* [4] presented a model based optical flow consistency to detect video forgery as inter-frame forgery will disturb the optical flow consistency. Tianqiang *et al.* [5] proposed a method using gray values to represent the video content and detected the tampered video including frame deletion, frame insertion and frame substitution.

In this paper, we propose a simple yet efficient method based on optical flow consistency to distinguish inter-frame forgeries from original videos. The basic idea of our method is that optical flows of original sequences are consistent while optical flows of inter-frame forgeries will have abnormal points. We first calculate the optical flow values between sequential frames of videos, and then use Support Vector Machine (SVM) [6] to classify original videos and inter-frame forgeries. We test our method on a large database, and results show that it is a method of high detection accuracy.

The rest of the paper is organized as follows. In Section 2 the optical flow generation is reviewed. Section 3 introduced how inter-frame forgery affects optical flow and the extraction of optical flow features. Experimental results and discussions are presented in Section 4 and Section 5 concludes the paper.

2. Review of Optical Flow

The Lucas Kanade optical flow is proposed by B. D. Lucas and T. Kanade. It has been widely used in layered motion, mosaic construction, face coding. Recently it is used in video inter-frame forgery detection [4] which is based on the assumption that for adjacent frames in original videos the optical flows are consistent, and inter-frame forgery will disturb this optical flow consistency.

The framework of the method [4] is as shown in Fig. 1.

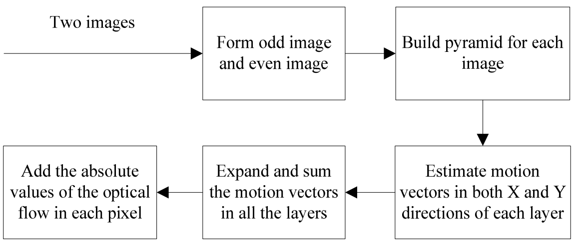


Fig. 1. The framework to extract the Lucas Kanade optical flow.

The main steps to extract the Lucas Kanade optical flow are as follows:

1. For each image, take its odd rows to form an odd image and its even rows to form an even image. The spatial sampling is conducted to reduce the computational complexity. For example, in Fig. 2(a) is the original image, and the odd image and even image are shown in Fig. 2(b).
2. Build a pyramid for each image. For example, in Fig. 3, the picture in the bottom is the original odd image, and the fours above it are the pyramid built on it. The picture above the bottom image is sampled every 2 rows and 2 columns from the original odd image. Accordingly, the other upper images are respectively sampled every 3/4/5 rows and the same columns from the original odd image.

(a) (b)

Fig. 2. Spatial sampling of original image.

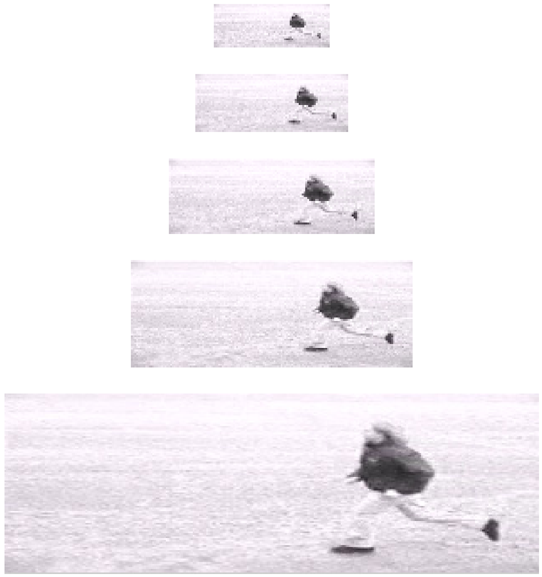


Fig. 3. 5-layer pyramid of odd image.

3. Estimate motion vectors in both X and Y directions of each layer in Fig. 3 from top to bottom between two images.
4. Expand the motion vector in the top layer twice and add it to its lower layer in both X and Y directions. Then smooth the sum of these two layers. Repeat these steps in each layer until the bottom layer. Finally, we obtain the optical flow between two odd images. The optical flows in odd image and even image are almost the same, while in original image is the sum of the two. The method calculating optical flows of odd images can reduce the computing complexity while keep the optical flow feature.
5. For two frames P and Q, two optical flow figures $OFX_{(P,Q)}$ and $OFY_{(P,Q)}$ which are optical flow vectors in the 2D space are computed by adding the absolute values of the optical flow in each pixel with equation (1).

$$S_{(P,Q)}(x) = \sum_{i=1}^{I} \sum_{j=1}^{J} OFX_{(P,Q)}(i,j), \qquad (1)$$

where $S_{(P,Q)}(x)$ is the sum of optical flow values between frame P and frame Q in the X direction, and

X can be replace with Y to calculate $S_{(P,Q)}(y)$, which is the sum of optical flow values between frame P and frame Q in the Y direction, I and J are the number of pixels in each row and each column of the optical flow figure.

3. Proposed Method

As we know, in [4] they supposed that the variability of optical flow in videos without tampering should be consistent, otherwise, the consistency would be destroyed by the deleted or inserted frames. So they used window based rough detection method and binary searching scheme to find out where the tampered frames are. In this paper, we propose a method using optical flow consistency feature to distinguish original videos and Inter-frame video forgeries. The difference between our method and the previous work [4] is that, the method in [4] was used for detecting where was tampered in a video. Although it mentioned that they considered the videos without abnormal points were original videos, but they didn't test their thought and give any experimental results [4]. While our method is for the purpose to identify whether a video was tampered and distinguish video forgeries from original videos.

Since their method cannot distinguish the original videos and forgeries directly, we improve their method by using normalization and quantization to obtain distinguishing feature of a fix length, and then use SVM to classify original videos and inter-frame forgeries.

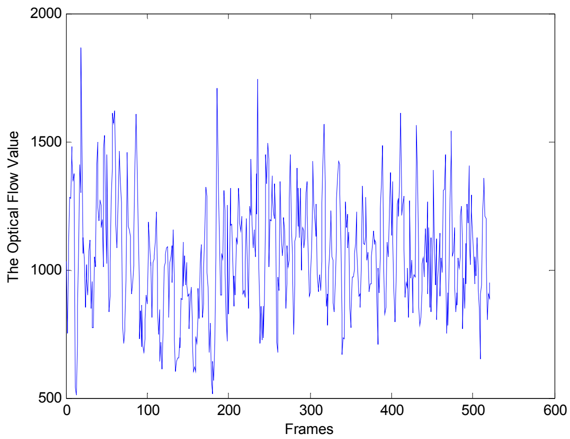
3.1. Analysis of Optical Flow Consistency for Original Videos and Inter-frame Forged Videos

Optical flow is efficient in depicting the continuity of frames. For a frame-tampered video, the optical flow would be changed a lot at the tampered point.

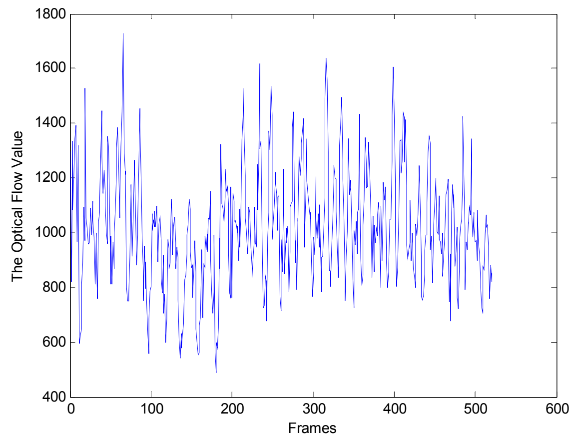
In the original video database, every frame is non-tampered. The continuous frames in the original video are as shown in Fig. 4.

Fig. 4. Three continuous frames from an original video.

These three frames are continuous in a video. We can see the motion of the people is small and the background almost has no difference. In fact, a whole video is composed by hundreds of frames. The fluctuation of optical flows between adjacent frames is shown in Fig. 5. The Fig. 5 (a) shows the fluctuation in X direction and Fig. 5 (b) depicts the fluctuation in Y direction. From Fig. 5, we can see that the optical flow values of sequential frames fluctuate in a small range. And the fluctuation in X direction and Y direction are very similar. That is to say, optical flows of original frames are consistent in either X direction and Y direction.



(a)

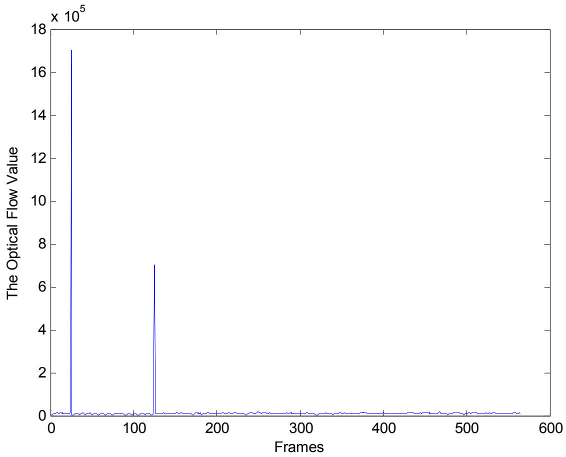


(b)

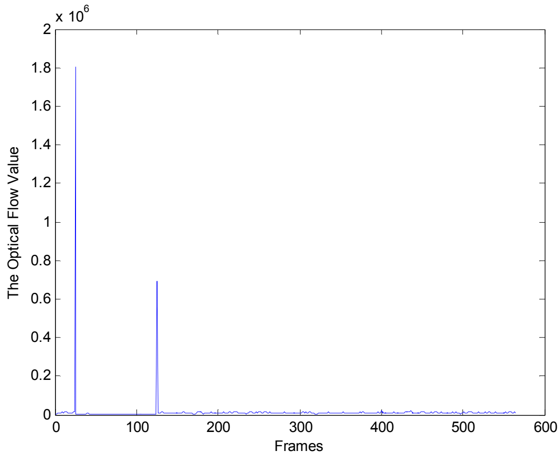
Fig. 5. The optical flow of an original video.

Videos in the 25-frame-inserted video database and 100-frame-inserted video database are inserted 25 or 100 frames somewhere. Fig. 6 shows four frames gotten from a 100-frame-inserted video. The first and forth images were the adjacent frames before frame insertion. Then we insert 100 frames between them. And the inserted 100 frames are continuous. In Fig. 6 the second and third images are the first and last frames of the video which was inserted to the original video. In a whole 100-frame-inserted video, the fluctuation of optical flows between adjacent frames is shown in Fig. 7. The Fig. 7 (a) shows the fluctuation in X direction and Fig. 7 (b) depicts the fluctuation in Y direction. From Fig. 7 we can see two peaks, which represent two tampered points. The front peak denotes the start point of the insertion, while the latter peak represents the end point. The fluctuations in these two points are much larger than that of other points.

Fig. 6. Four continuous frames from a 100-frame-inserted video.



(a)



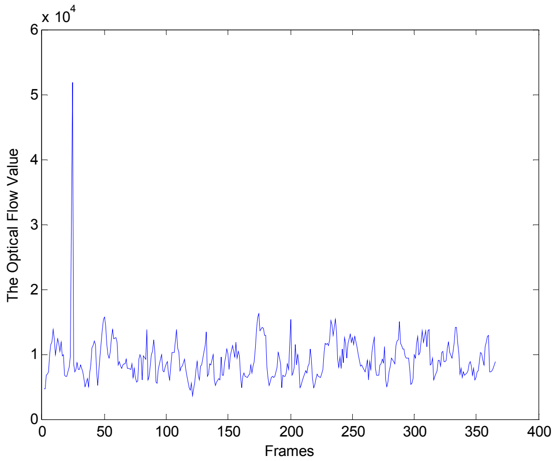
(b)

Fig. 7. The optical flow of a 100-frame-inserted video.

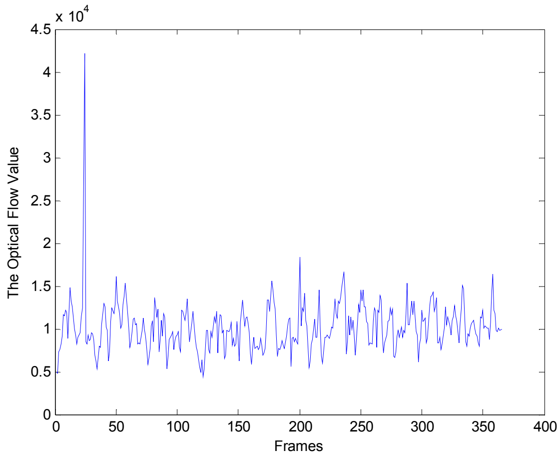
Similar to the frame-inserted video, in the 25-frame-deleted video database and 100-frame-deleted video database, every video is deleted 25 or 100 frames somewhere. Fig. 8 shows three frames gotten from a 100-frame-deleted video. The first two images are the frames before frame deletion and the third image is the frame after deleting 100 frames from the original video. In fact, we cannot find much difference between the last two images. In a whole 100-frame-deleted video, the fluctuation of optical flows between adjacent frames is shown in Fig. 9. From Fig. 9 we can see one peak. The peak denotes the deletion point, where the fluctuation of optical flows is much larger than that of other points.

3.2. Framework of Inter-frame Forgery Identification Scheme

Fig. 8. Three continuous frames from a 100-frame-deleted video.



(a)



(b)

Fig. 9. The optical flow of a 100-frame-deleted video.

In this paper, an optical flow consistency based inter-frame forgery identification scheme is proposed. The framework of our method is as shown in Fig. 10.

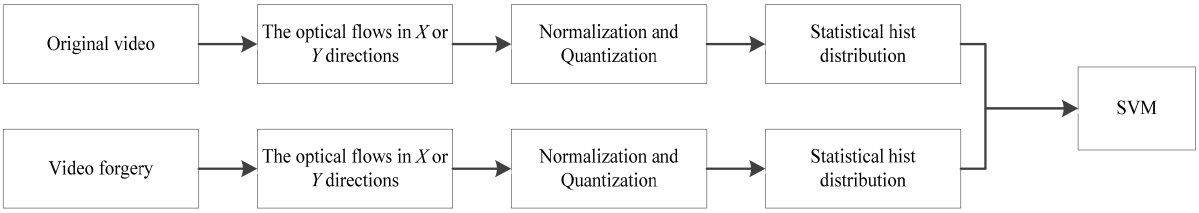


Fig. 10. The framework of video inter-frame forgery identification.

The detailed scheme of our method is as follow. Since the method of extracting optical flow consistency feature in *Y* direction is the same as in *X* direction, we just take the feature extraction in *X* direction for example.

1. Calculate the optical flows between adjacent frames.

The method is based on the extraction of Lucas Kanade optical flow. Equation (1) is used to calculate optical flows in *X* direction between two frames. *X* can be replaced with *Y* to calculate optical flow in *Y* direction. For a video with *M* frames, get a (M-1)×2 matrix to store the optical flows of the video, where the 1st column stores the optical flows in *X* direction and the 2nd column stores them in *Y* direction.

2. Normalize and quantize the optical flows.

For the 1st column of the matrix, find the maximum value *m* and divide every element in the column by *m*. Then quantify all the elements into *D* quantization levels. As all of them are distributed from 0 to 1, the quantization interval is 1/*D*.

3. Count the statistical distribution of the quantified optical flows.

After the normalization and quantization steps, the *M*-1 elements are all discrete values from 1/*D* to 1 (1/*D*, 2/*D*, …, 1). Count the distribution of the discrete values into a D×1 vector. For a video database with *N* videos, build an array contains *N* vectors of the statistical distribution to represent the optical flow consistency feature of all the videos in the database.

4. Distinguish original videos and video forgeries with SVM.

Put the optical flow consistency feature of the original videos and video forgeries to the SVM and distinguish the different kinds of videos. Repeat 20 times and get the average classification accuracy.

4. Experimental Results

In experiments, we use five video databases. One is original video database. The other four are tampered video databases, of which each separately contains the videos inserted 25 frames, inserted 100 frames, deleted 25 frames and deleted 100 frames. There are 598 videos with still background and a little camera shake in each video database (N=598).

4.1. Experimental Setting

In our experiments, we use SVM of polynomial Kernel [6] as the classifier.

To train the SVM classifier, about 4/5 of the videos are randomly selected as the training set (480 originals and 480 forgeries). The rest 1/5 form testing set (118 originals and 118 forgeries). The experiments are repeated for 20 times to secure reliable classification results.

4.2. Results and Discussion

We extract optical flow consistency features of the five video databases, and classify original videos and each of the four kinds of tampered videos separately. The average classification accuracy is as shown in Table 1.

Table 1. Classification accuracy between original videos and forgeries.

Forgery Database	*X* direction	*Y* direction
25-frame-insertion	98.41 %	98.60 %
100-frame-insertion	98.20 %	98.54 %
25-frame-deletion	86.82 %	86.02 %
100-frame-deletion	92.61 %	88.56 %

Obviously, the proposed method is efficient to identify whether a video was tampered. As expected, the classifying accuracy between originals and frame-inserted forgeries is higher than that of frame-deleted forgeries. But even the classifying accuracy between original videos and 25-frame-deleted forgeries is 86.86 % in *X* direction and 86.02 % in *Y* direction, which is the lowest level of the four experiments.

We then try to mix the four kinds of forgeries and classify them from originals. The result is efficient, too. The accuracy is 91.37 % in *X* direction and 88.44 % in *Y* direction.

Inspired by this, we further try to classify frame-inserted forgeries and frame-deleted forgeries. With the same method, we classify the 25-frame-inserted videos and 25-frame-deleted videos, as well as 100-frame-inserted videos and 100-frame-deleted videos. The classifying result is as shown in Table 2.

Table 2. Classification accuracy of two kinds of forgeries.

Forgery Database	*X* direction	*Y* direction
25-frame-insertion and 25-frame-deletion	91.72 %	90.00 %
100-frame-insertion and 100-frame-deletion	89.83 %	92.63 %

We can see that the classification accuracy still stay high. The proposed method is effective in classifying two kinds of forgeries. Then we mix the 25-frame-inserted videos and 100-frame-inserted videos, as well as 25-frame-deleted videos and 100-frame-deleted videos. And classify the two kinds of mixed forgeries. The accuracy is 97.75 % in X direction and 98.67 % in Y direction.

To sum up, our method is efficient in classifying original videos and forgeries as well as different kinds of forgeries.

5. Conclusions

In this paper, we extract the optical flow consistency as distinguishing features to classify original videos and forgeries. The classifying accuracies are high in all of the experiments indicate that the proposed method is efficient in classifying original videos and forgeries yet different kinds of video forgeries.

In future work, we will combine the optical flow consistency features in X direction and Y direction. And in view of the fact that the videos we use in the experiments are under still background, we will build a new video database with moved background.

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