Raindrop Detection from In-Vehicle Video Camera Images for Rainfall Judgment

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Abstract

In this paper, we propose a method to detect raindrops from in-vehicle camera images and recognize rainfall using time-series information. We aim to improve the accuracy of raindrop detection by averaging the test images and frame-matching the result of raindrop detection in multiple adjoining frames. According to an evaluation experiment, raindrops were detected precisely enough for automatic wiper control by the proposed method.

1 Introduction

Recently, there has been much activity in the development of driver assistance systems that use computers and various sensors [2][3][4], especially in-vehicle camera systems, since images taken from such systems contain important visual information [5]. While humans can visually recognize rapidly changing traffic conditions when driving, in-vehicle cameras are also showing promise in capturing similar visual conditions. The following are examples of driver-assistance systems that use video images to impart traffic-related information: self-steering from white-line recognition [6]; distance adjustment between cars from leading-vehicle recognition [7]; automatic braking systems from pedestrian recognition [8]; and so on.

A close relationship exists between driver assistance and weather recognition [9] [10]. Since in rain driving is more difficult than in fair conditions, accident rates dramatically increase. Moreover, weather changes temporally and spatially, so we believe that it is important to develop techniques that recognize weather in real time by in-vehicle sensors for driver assistance. Actually, auto-wiping systems using rain recognition, controlled by a so-called "rain sensor," are already implemented on some commercially available cars. However, employing a specific sensor for each purpose increases the number of sensors, which is undesirable from the viewpoints of appearance, space, cost, and maintenance. Since raindrops scatter light, a rain sensor detects rainfall by observing changes in the amount of light received from infrared rays emitted from an LED. However, the target region for detection covered by the sensor is small, so it does not necessarily reflect changes in the visibility from a driver's perspective. An in-vehicle camera, on the contrary, covers most of the driver's visual field since it targets the entire windshield.

We have previously proposed a method of detecting raindrops from in-vehicle camera images by template matching using the subspace method, which extracts image features of raindrops (Fig. 1) and judges rainfall from the detected results [1]. This method suppresses false detection of raindrops by limiting the target region to the sky region, which does not have complex patterns in the background as exemplified in Fig. 2. However, it was ineffective in cases where the ratio of sky region to the entire image is small, such as in an urban district crowded with high buildings or in a tunnel.

Hence, in this paper, we propose a method using time-series information that does not require region restriction for stable raindrop detection. While positions of raindrops on the windshield do not move in relation to the in-vehicle camera, the external view does change when the car is moving. Because of this, raindrops are emphasized by the change in background. Taking advantage of this phenomenon, we attempt to improve the detection accuracy by focusing on the temporal change of the image with raindrops, which is difficult to detect from a single frame due to the influence of complex backgrounds.

We describe the proposed method in Sect. 2 and evaluate

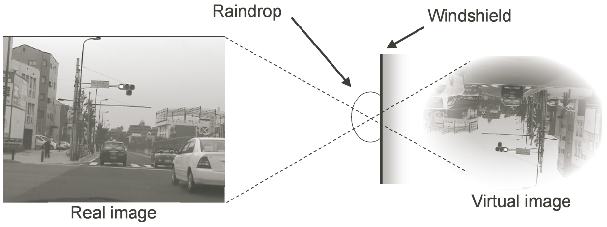


Figure 1. Image features of a raindrop.

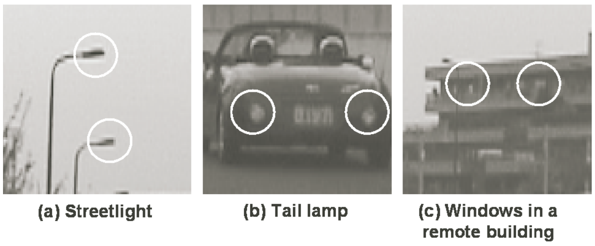


Figure 2. Objects whose characteristics resemble the image features of a raindrop.

the results in Sect. 3. Then the paper concludes in Sect. 4.

2 Raindrop detection method

2.1 Overview of the process

As Fig. 3 shows, our method is composed of three stages: Learning, Detection, and Judgment. In this section, we describe the flow and the improvement of the method by using time-series information. The previous method detected raindrops from only the sky region in an input image. However, in this approach we restrict the application of the method to in-vehicle camera images with a relatively large sky region. The method we propose in this paper revises this problem by emphasizing the raindrops using time-sequence information in the detection stage.

A. Learning Stage

First, as a training set, a rectangular region circumscribing each raindrop is cut manually from images of a windshield taken in rainy weather. Only raindrops are cut out to obtain stable image features in the sky region. A total of *K* images are prepared for learning. Next, they are normalized in size to width *W* and height *H*, represented as one-dimensional vectors, which are then normalized so that they become unit vectors with means of 0, represented as $\mathbf{x}_i = (x_1, x_2, \cdots, x_N)^T$, where $N = W \times H$. Let a matrix arranged by *K* randomly selected vectors from the test

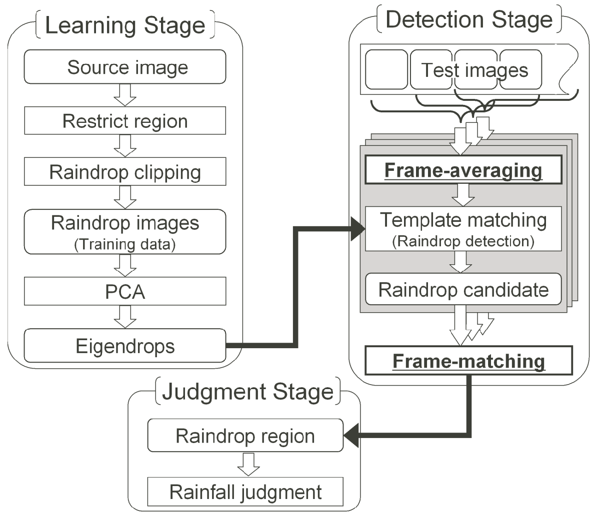


Figure 3. The flow for rainfall recognition.

images be $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_K]$ and its covariance matrix be $\mathbf{Q} = \mathbf{X}\mathbf{X}^T$. The eigenvectors $\{\mathbf{e}_1, \mathbf{e}_2, \cdots, \mathbf{e}_R\}$ corresponding to the largest *R* eigenvalues of $\mathbf{Q}$ are selected as the feature vectors. A subspace generated by these eigenvectors is called an ”eigendrop.”.

B. Detection Stage

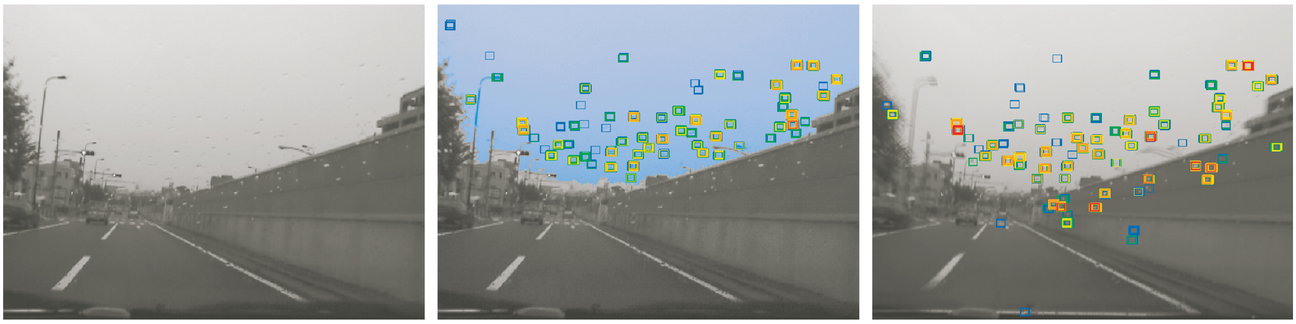
Raindrops are detected from the test images in the following way. First, an averaged image is made from multiple sequential frames obtained from the input video. In the averaged image, we focus on rectangular areas of size $W \times H$. Let the area be represented by a one-dimensional normalized vector $\mathbf{a}$. Next, we compute the degree of similarity $S(\mathbf{a})$ of a with the eigendrops, where $S(\mathbf{a})$ is defined as: $S(\mathbf{a}) = \sum_{r=1}^{R} (\mathbf{a}, \mathbf{e}_r)$ ((**x**,**y**): inner product). The area is detected as a raindrop candidate if $S(\mathbf{a})$ is larger than a threshold value. They are detected by computing $S(\mathbf{a})$ throughout the frame by shifting the rectangular area in focus. Finally, raindrop regions are obtained by frame-wise matching the raindrop candidates.

C. Judgment Stage

Rainfall is judged by counting the number of raindrops detected in stage B. If the number of raindrops in the image exceeds a certain threshold, we judge that it is raining, and not raining if it does not.

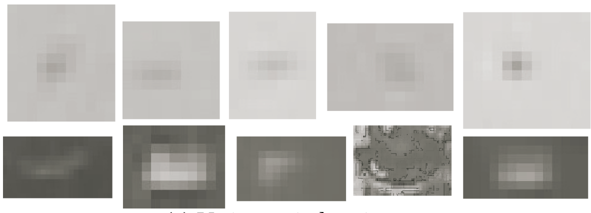
2.2 Raindrop detection from an entire image by averaging adjoining frames

The original method of raindrop detection described in Sect. 2.1, had a risk to false-detect non-raindrop regions

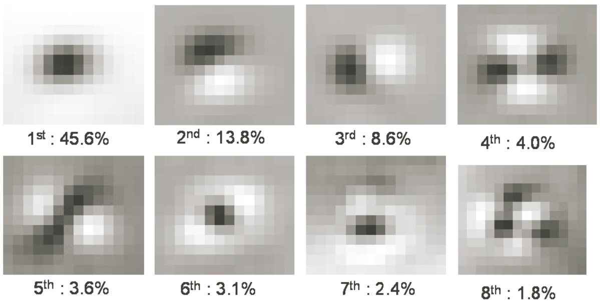


(a) Test image (b) Sky region restriction (c) 5 frame-averaging + 10 frame-matching

Figure 5. Raindrop detection result.



(a) Various raindrop images



(b) Eigendrops and their contribution rates

Figure 4. Examples of raindrop images and eigendrops.

as raindrops by the influence of complex background patterns. Hence, in thsi paper, we propose to emphasize the raindrops by averaging multiple adjoining frames in the detection stage. By detecting raindrops from the averaged image, robust raindrop detection from the entire frame is expected.

2.3 Reduction of false detection by frame-matching raindrop candidates

If positions of raindrops are stable on the windshield, a raindrop should be detected at the same position in the next frame. On the other hand, a position of a falsely detected raindrop by complex background patterns should be instable. Hence, we considered that false detection could be reduced by matching the results of raindrop detection across adjoining frames. An AND operation is applied to raindrop candidates across multiple adjoining frames.

3 Evaluation of raindrop detection

3.1 Conditions

We mounted a digital video camera inside a car and captured video footage while driving (30 fps, 640×480 pixels, grayscale).

The proposed raindrop detection method was applied to each frame of the input video sequence. The recall and precision ratios for raindrop detection were then calculated in order to evaluate the detection accuracy. In the learning stage, the eigendrops were made from 500 raindrop images. Template matching in the detection stage was achieved by shifting templates (eigendrops) one pixel at a time.

Figure 4 shows the clipped raindrops and the eigendrops created from them. The subspace dimension was six when they were made.

3.2 Results

Figure 5 shows examples of raindrop detection in various experimental conditions, while Fig. 6 depicts the recall and precision curves. The recall and precision ratios represent the degree of detection failure and false detection, respectively; if the detector performs well, each ratio will be close to 1.0. When the number of ground-truth raindrop areas is A, the number of detected raindrop areas is B: Precision $= (A \cap B/B)$, Recall $= (A \cap B/A)$. When the number of frames used for averaging increased, although recall improved significantly, the precision fell somewhat. Furthermore, when the number of frames used for frame matching increased, although precision improved, recall dropped.

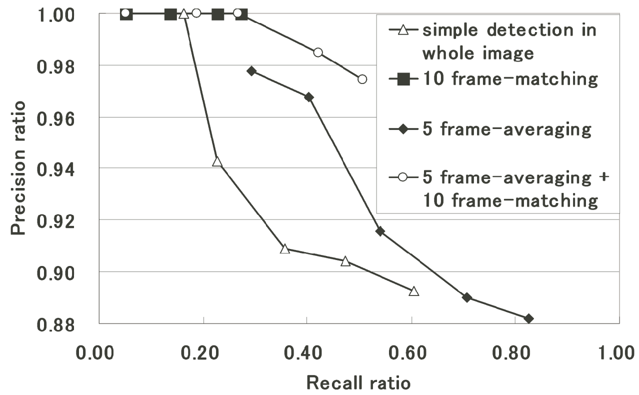


Figure 6. Accuracy of raindrop detection by the proposed method.

We checked the condition that recall improved the most when precision exceeded 0.95 by changing the number of frames used for the averaging and frame matching. The best result was a precision of 0.97 and a recall of 0.51 when the similarity threshold was 0.70, 5 frame-averaging, and 10 frame-matching.

3.3 Disscussion

The precision is more important than the recall for practical use as a windshield wiper controller, since incorrectly recognizing raindrops and letting the windshield wipers malfunction must be avoided. However it is also a problem when recall is too low. While this result was obtained from images covering the entire field of view, it was not inferior to the result gained by our previous method, in which the target region for raindrop detection was restricted to the sky region and gave a precision of 0.97 and a recall of 0.59.

Since the success rate for rainfall judgment using the result of raindrop detection from the sky region reached 89%, the proposed method should also be able to judge rainfall similarly.

4 Conclusion

In this paper, we proposed an improved method that detects raindrops from in-vehicle camera images with no restriction to the detection region. Raindrops were detected precisely by averaging the input images and frame-matching the result of raindrop detection.

Acknowledgment

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