

Rainy Weather Recognition from In-Vehicle Camera Images for Driver Assistance

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Abstract— We propose a weather recognition method from in-vehicle camera images that uses a subspace method to judge rainy weather by detecting raindrops on the windshield. “Eigendrops” represent the principal components extracted from raindrop images in the learning stage. Then the method detects raindrops by template matching. In experiments using actual video sequences, our method showed good detection ability of raindrops and promising results for rainfall judgment from detection results.

I. INTRODUCTION

Recently, driver assistance with computer and various sensors are being actively developed, especially in-vehicle cameras systems since such images contain important visual information. When driving, we visually recognize rapidly changing traffic conditions. The following are examples of driver-assisted systems that use video to impart traffic-related information: self-steering from white line recognition; distance adjustment between cars from leading vehicle recognition; automatic braking systems from pedestrian recognition; notification of traffic signs, and so on. Therefore image processing methods that enable such assistance systems are being pursued [1][2].

A close relation exists between driver assistance and weather recognition. Since in such adverse weather conditions as rain, snow, or fog, driving is more difficult than during fair conditions, accident rates dramatically increase. Weather changes temporally and spatially, so we believe that it is important to develop techniques that recognize weather in real time by sensors equipped in cars for driver assistance. Auto-wiping, braking assistance, and auto lighting fog lamps are examples of potential assistance systems to be realized by this technique.

In this paper we focus on rain recognition, even though actually an auto-wiping system is already enabled for rain recognition using a so-called “rain sensor.” But employing a specific sensor for each purpose increases the number of sensors which is undesirable from the viewpoint of appearance, space, cost, and maintenance. Since raindrops scatter light, a rain sensor can detect rainfall by observing changes in the

amount of light received from infrared rays with a LED. However, the detection region covered by the sensor is small, so it does not necessarily reflect changes in the visibility of a driver. On the other hand, an in-vehicle camera covers most of the driver’s visual field since it targets the entire windshield.

Hence we aim to recognize rainy weather by extracting the image feature characteristics of rain from in-vehicle images. Concretely, we propose the following methods in this paper:

- Detection of raindrops on the windshield from in-vehicle camera images.
- Assessment of rainy or fair weather from the results.

As an image feature, we focused on raindrops on the windshield. We used a subspace method to extract raindrops in order to detect changes of visual conditions during rain. In Section 2, we introduce works related to weather recognition using image analysis and pattern matching by a subspace method. We describe our proposed method in Section 3 and report experimental results in Section 4. Then we discuss the results in Section 5 and summarize this paper in Section 6.

II. RELATED WORKS

2.1. Weather recognition by image processing

Works related to weather recognition by image processing include [3], who proposed a method based on physical models to improve the contrast of images under adverse weather conditions, especially foggy images. [4], which is also related to fog, attempts to evaluate visibility in foggy images by proposing a method that evaluates the relation between manually observed road visibility and image features of an image recorded by a digital still camera. This work makes use of a security camera along roads whose purpose is mainly for the administration of the road. However, since the purpose of our work is different, we mount an in-vehicle camera shooting forward.

Heretofore rain weather recognition methods that use images have received little attention because it is easy to detect rain with a sensor. However, we believe that, for driver-assisted techniques, it is important to recognize rainy weather mainly from images that reflect visual conditions.

2.2. Subspace method for pattern recognition

In this paper, we use a “subspace method” widely used in pattern recognition fields. A subspace method extracts features using principal component analysis (PCA) from images that

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have common features and use them to match the patterns.

[5] proposes, for example, a parametric eigenspace method which continuously represents two-dimensional image fluctuations in response to the directions of three-dimensional objects or changes of light source as a manifold on the subspace (eigenspace), which is composed of image eigenvectors. In addition, [6] and [7] use the subspace method to recognize human faces.

III. PROPOSED METHOD

3.1. Overview

In this paper, we detect raindrops on a windshield using image features from PCA that represent the essential characters of raindrops. Raindrop image features are defined as having the following characteristics:

- Edges that feature a raindrop outline.
- Blurry edges behind raindrops.
- Refraction of light by raindrops.

Raindrops have a uniform shape; any drop basically appears circular when seen through a windshield, and although a raindrop itself is clear and colorless, it is visible due to the reflection of its background as in Figure 1. Raindrop texture varies since the background reflecting them varies. However we believe that raindrops share at least the above features.

Figure 2 shows the flow of our method. We propose two methods:

[Method 1] Method 1 is composed of three stages: learning, detection, and judgment. We create a raindrop template, an “eigendrop,” in advance by PCA from images cut squarely in the learning stage. In the detection stage, we cut a rectangular area from the test set and compare it with the eigendrops. The rectangular area is shifted in a raster scan style. Finally, in the judgment stage, we assess the weather either as fair or rainy from the detection results. The concrete process is explained in detail in 3.2..

[Method 2] Method 2 restricts the target area for training and detection. This process is also described in 3.3.

3.2. Method explanation

A. Learning Stage

First, as a training set, rectangles circumscribing each raindrop are cut manually from images of a windshield taken in rainy weather. Let these rectangles represent raindrop regions. A total of K images are prepared for training. Next, they are normalized in size to width W and height H , represented as 1-dimensional vectors, which are then normalized so that they become unit vectors with means of 0, represented as: $\mathbf{x}_i = (x_1, x_2, \dots, x_N)^T$, where $N = W \times H$. Let a matrix arranged by K randomly selected vectors from the test images be $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_K]$ and its covariance matrix be $\mathbf{Q} = \mathbf{X}\mathbf{X}^T$. We compute the largest R eigenvalues of \mathbf{Q} and the eigenvectors $\{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_R\}$ corresponding to them. A subspace made by these eigenvectors as bases are the eigendrops.

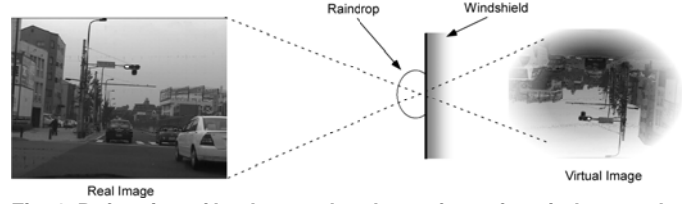


Fig. 1. Refraction of background to the surface of a raindrop on the windshield

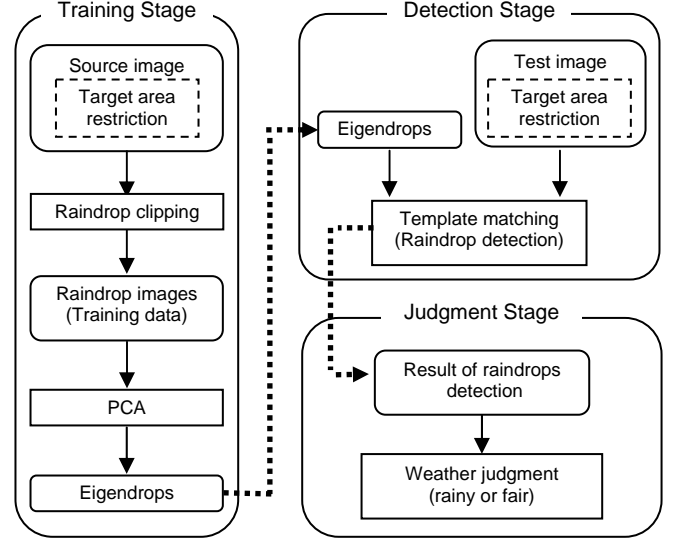


Fig. 2. Flowchart

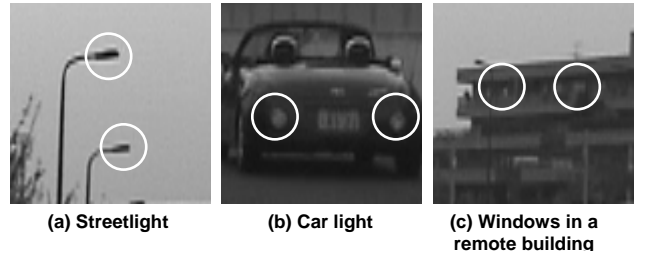


Fig. 3. Objects whose characteristics resemble the image features of a raindrop

B. Detection Stage

Here, we explain the raindrop detection from the test images. In a test image, we focus on rectangular areas with the size of $W \times H$. Let the area be represented by an one-dimensional normalized vector \mathbf{a} . Next, we compute the degree of similarity $S(\mathbf{a})$ with the eigendrops. $S(\mathbf{a})$ is defined as:

$$S(\mathbf{a}) = \sum_{r=1}^R (\mathbf{a}, \mathbf{e}_r)^2 \quad ((\mathbf{x}, \mathbf{y}) \text{ denotes an inner product}).$$

We detect the area as a raindrop if $S(\mathbf{a})$ is larger than a threshold. We detect raindrops in the test set by computing the degree of similarity with eigendrops while shifting the focused rectangular area.

C. Judgment Stage

We judge rainfall by counting the number of detected raindrops at the above stage. If the number of raindrops exceeds

a certain threshold, we judge that it is raining and fair if it is not.

3.3. Restriction of target area for raindrop detection

In the preceding section, we did not restrict the target area for detection, as described in Method 1. However it needs further refinement to improve the detection accuracy. The advantages of the restriction are:

- Suppression of false detection due to background texture.
- Improved detection accuracy by extracting stable image features.
- Reduction of computation time for template matching.

Concretely, as the target area for detection, we extract the sky area assuming that, in that area, the background change is comparatively small. We did the same thing when making eigendrops in the learning stage in this method.

Outside the sky area, if there are objects whose characteristics resemble the image features of raindrops as in Figure 3, false detection is possible in the detection stage. We also contend that in the learning stage the features extracted by PCA are unstable since a large part of the texture changes in the background contains many image features without raindrops. In addition, increasing the processing speed is a major goal of the restriction.

IV. EXPERIMENTS

In this section, we applied the proposed method to an image taken with an in-vehicle camera. We evaluated the accuracy of the raindrop detection and weather judgment using two images taken on different days. First we explain the process of each experiment and then discuss the results.

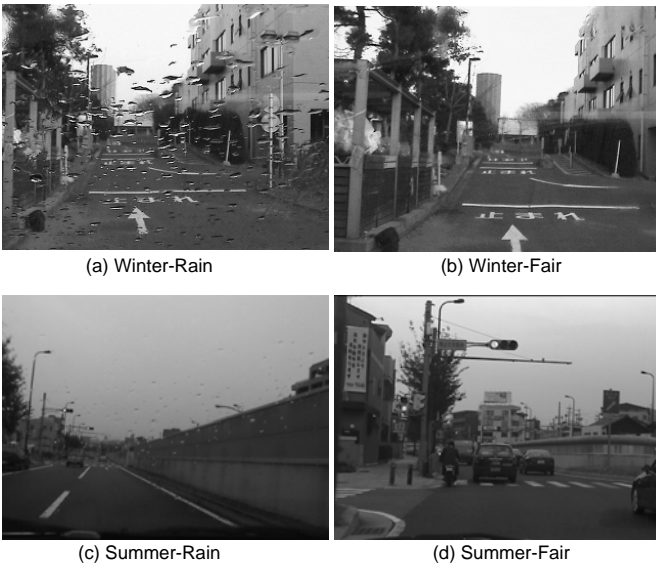


Fig. 4. Examples of in-vehicle camera image in various conditions

4.1. Experimental method

We used the following two kinds of images for the experiment (Figure 4):

[Data1] An image taken in winter when large raindrops were on the windshield.

[Data2] An image taken in summer when a light rain was falling.

We mounted a digital video camera to a car and took both images (30 fps, 640 x 480 pixels, grayscale).

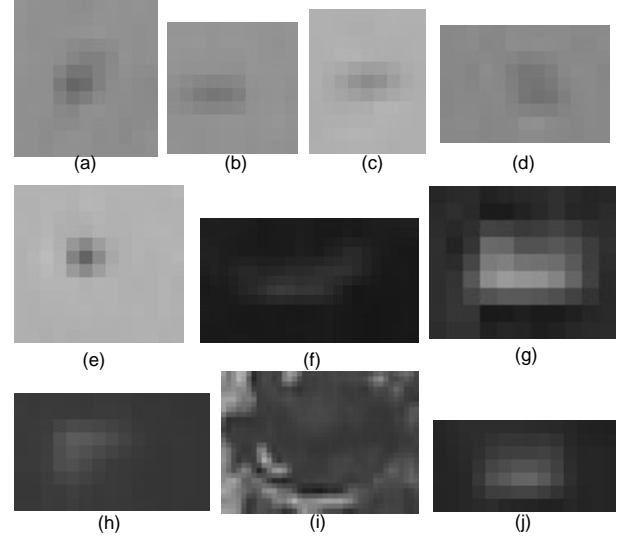


Fig. 5. Various raindrop images: (a)-(e) Cut from the sky area; (f)-(j) Other areas

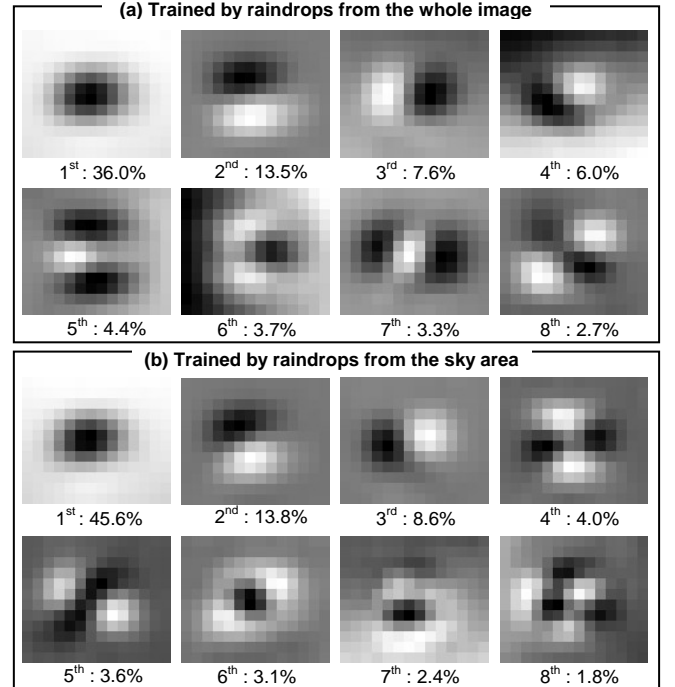


Fig. 6 . Eigendrops and their contribution rate: Raindrop regions were cut from (a) the whole image, or (b) the sky area.



(a) Method 1 (see whole image)

(b) Method 1 (see sky area)

(c) Method 2

Fig 7. Raindrops detected when both training and detection were applied to the whole image ($S(a) \geq 0.78$)



(a) Rain

(b) Fair

(c) Wiping

Fig 8. Raindrops detection when both training and detection were applied only to sky area. ($S(a) \geq 0.78$)



(a) Before wiping

(b) Wiping

Fig. 9. Change of number of detection by wiping

We made eigendrops from each training image set and applied the raindrop detection to each frame of the input video sequence. Then we computed recall and precision ratios of the raindrop detection to be used as indicators of the detection accuracy. In the learning stage, we made eigendrops from 500 raindrop images. Template matching in the detection stage was achieved by shifting templates (eigendrops) 1 pixel at a time.

We also experimented rainy weather judgment using the results from the raindrop detection. First, we chose at random 100 images of both fair and rainy weather. Next, we determined the threshold (the number of detected raindrops). Then the number of images judged as correct weather was counted. We observed changes of weather judgment by changing the threshold.

4.2. Experimental results

Figure 5 shows part of the raindrop images used for the experiment with data 2. Figure 6 shows the created eigendrops. The subspace dimension was six when they were made. With data 1, we obtained good results as exemplified in Figure 9. Recall was 0.24 and precision was 0.87 in Figure 9(a). 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.

With data 2, although we did not obtain good results using method 1, we obtained good results using method 2. Figure 7 shows an example of results of the raindrop detection applied to data 2. With method 1, numerous false detections appeared near the boundary lines of objects as in Figure 7(a). However we can obtain good results when we observe only the sky area. Figure 10 compares the detection result between method 1 restricted to the sky area and method 2. In general, the higher the recall ratio is, the lower the precision is. Although the precision in method 1 begins decreasing where the recall is around 0.3, method 2 keeps high precision even when the recall is close to 0.9. As seen in Figure 10, method 2 is always better than method 1.

Figure 11 shows the results of fair or rainy weather judgments applied to the test set (data 2) while changing the detection number threshold, from the results of the raindrop detection by method 2. We judged the weather correctly by about 90 percents when the similarity threshold was set to 0.80 and the detection number threshold was set to around 5, for example.

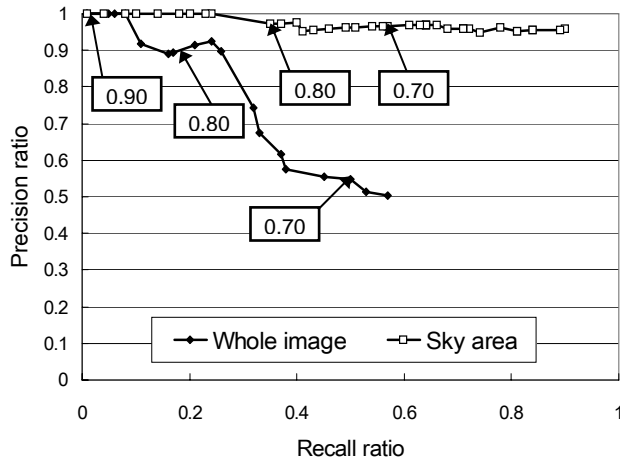


Fig. 10. Accuracy of raindrop detection: When the number of ground truth raindrop areas is A , the number of detected raindrop areas is B : $Precision = (A \cap B) / B$, $Recall = (A \cap B) / A$. Numbers in boxes represent similarity thresholds.

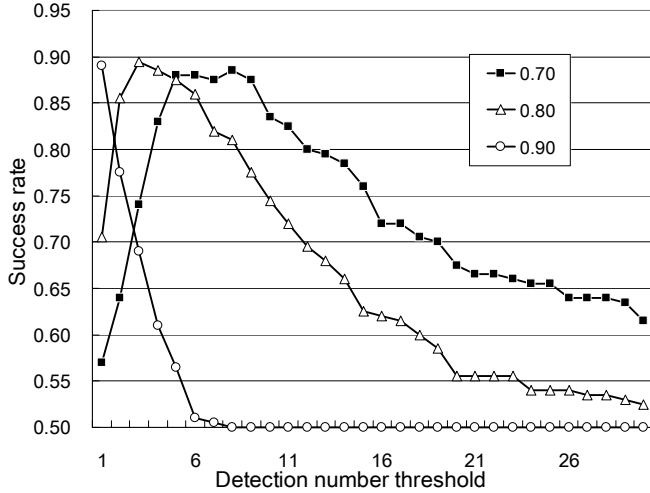


Fig. 11. Success rate of rainfall judgment by the changing threshold (data 2, method 2): We used 100 images for both fair and rainy weather, and judged by the number of detected raindrops in each image. The three lines represent the graph of different similarity thresholds.

V. DISCUSSION

5.1 Detection accuracy and rainfall judgment

First, we considered why detection accuracy was low when method 1 was applied to data 2. The 4th principal component in Figure 6(a), eigendrops, shows a strong edge feature in the vertical direction, and the 6th shows it in the horizontal direction. As a result, false detections occur since the similarity between eigendrops and the areas that include such edges increases as in Figure 7(a). Since raindrops are small and their edges are weaker in data 2 than in data 1 as in Figure 4, it is hard to recognize raindrop shapes in an area where the background texture is complex. For such reasons, we believe that the image feature of a typical raindrop were not clearly extracted.

On the other hand, in method 2, which restricts the detection area, detection accuracy improved since the principal components were extracted stably as shown in Figure 10. However, the uses of method 2 are limited, since it is difficult to detect raindrops when the sky area is small.

Since in-vehicle camera images are sequential, raindrop positions are relatively stable and small compared to the background motion when driving if the camera is fixed. In the future, we plan to obtain stable raindrop features using inter-frame information.

Rainfall judgment was mostly successful even if raindrop detection numbers were small, for example when the similarity threshold was set to 0.8. Since the recall ratio of raindrop detection using this threshold corresponds to only around 0.3 in Figure 10, rainfall judgment requires high precision ratio but not high recall ratio. This indicates that false detection should be minimized but, oversights are not crucial. Hence we believe that the raindrop detection method that we proposed is effective to judge rainy or fair weather.

5.2 Judgment of rainy or fair weather at night

In the previous experiments, our method targeted rainy weather recognition from daytime images. Since image features vary by time of day, we will discuss image features that are effective at night.

In rainy weather images at night, the refraction of light is characteristic (Figure 12). A night image is dark, and almost nothing could be seen without a light or the lighted area. Raindrops were also difficult to be seen on the windshield away from the lighted area. Streetlights or car lights for example, are seen as many small lights distributed over the surroundings of a large light by the refraction of raindrops on the windshield (Figure 12(a)). Rainy weather recognition may be improved if this feature can be recognized from an image.

We extracted areas with high brightness, i.e., light areas, and classified them into the light source and the refracting light areas. By checking around the light source area, we determined rainy weather by the existence of many refracted light areas. Figure 13 shows the success rate of rainfall judgment by changing the thresholds (numbers of refracted light areas).

VI. CONCLUSION

In this paper, we proposed a method to recognize weather conditions when driving by detecting raindrops on the windshield from in-vehicle images that use a subspace method. In experimental results using actual images, we obtained good results when extraction of the image features was easy. By restricting the detection to the sky area, we also achieved good results when the detection was difficult. Hence we confirmed the efficacy of our method.

In the future we will consider a robust method that detects raindrops in background areas using inter-frame information. In addition, although we restricted the target area for the raindrop detection using image features, we considered using

visible positional information, which can be obtained from a so-called “eye camera.” Therefore in the detection area we will include the area near the view of drivers. Moreover, evaluation of the method under various rainy weather situations according to time, place, and rainfall is another subject.

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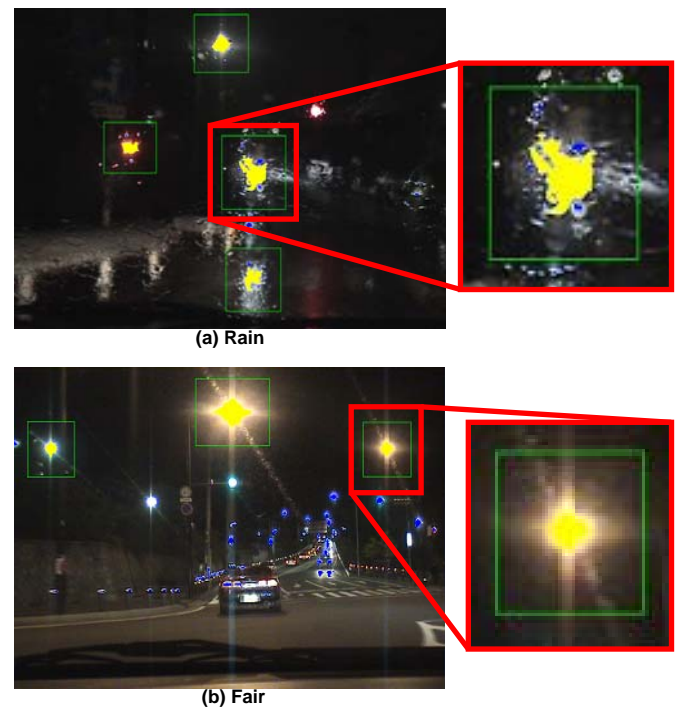


Fig. 12. Nighttime rainy weather image: refracted light areas are seen around the light source area.

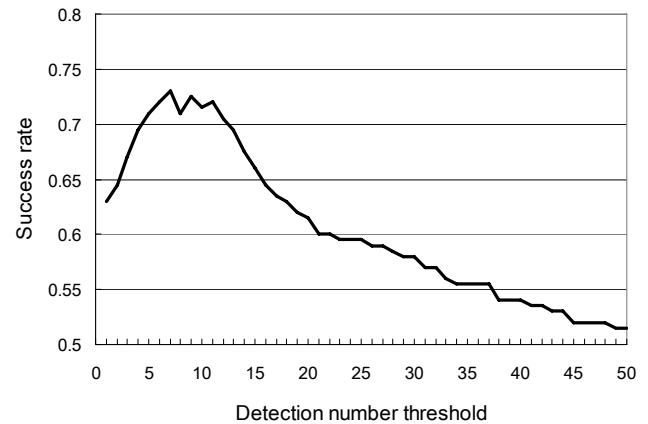


Fig. 13. Success rate of rainfall judgment at night by changing the threshold: We used 100 images for both fair and rainy weather, and judged by the number of detected raindrops in each image.