

Classification of Wet/Dry Area Based on the Mahalanobis Distance of Feature from Time Space Image Analysis

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Abstract

In this paper, we propose a method to detect a wet area on the road from a single camera. We create a virtual reflection image from the input image and the 3D shape information. We do not propose about the 3D reconstruction method. To classify the areas, we compute the time space image on each area and classify them based on the mahalanobis distance from the training data.

1 Introduction

Recently, there are many researchers who work in the area of Intelligent Transport System (ITS). Specially, there is a great interest in the assist system for a safety drive which is mounted on the vehicle. The ITS can be divided into 2 categories, whether the system itself is mounted on the vehicle[6], or not[2, 3]. The system mounted on the vehicle will process the information collected from the outside of the vehicle, and estimate or detect useful information for the safety drive.

In this paper, we propose a method which classifies the area on the road to dry, wet or indeterminable area. Proposed method uses the information obtained from a single camera, fixed on the vehicle. Wet detection is based on the statistics of the reflection intensity.

A wet road is dangerous compared to a dry road since the surface of the road is slippery. In previous works, many researchers used a polarization camera [2] or a camera fixed above the road[2, 3]. Compared to them, the proposed method uses a normal camera fixed on the vehicle. This is a big difference against the previous methods. The polarization lens is unnecessary, and camera can move as long as it is fixed on a vehicle. The road map of the wet area will be created after the vehicle runs on the road.

In a near research field, polarization lens is used in the reflection analysis. Miyazaki *et al.* proposed a reflection analysis method to estimate the surface shape of the transparent objects[4]. Yanghai *et al.* proposed a reflection separation method based on multi-layer method[5]. The difference between the proposed method is that they separate the reflection. On the other hand, the proposed method computes the incident light from a single image.

Our method is composed by 3 steps. First, the computer a spatial temporal image by registering the top-

view images. Next, the method computes the incident light corresponds to each area. Finally, the area is classified to 3 types: wet, dry or indeterminable. The originality of the proposed method is the estimation of the incident light by using the environmental shape information. The incident and reflection is obtained by single camera.

The rest of this paper is organized as follows. Section 2 explains the wet road surface reflection attribution and the incident lights. Section 3 explains the method in each step, and Sec. 4 demonstrates the efficiency of the proposed method.

2 Theory

In this section, the reflection attribute and the computation of the incident light is described.

2.1 Specular reflection

When we compare between a dry asphalt road and a wet surface, the largest difference is the reflection. The dry road looks grey, and the color is uniform along the road. The color is uniform since the surface has strong random reflection attribute. Thus, the reflection on the dry road is independent from the angle.

On the other hand, wet road surface shows different reflection attribute compared to the dry one. A damp road surface looks darker than the dry surface. This reflection light is trapped inside the moisture on the surface. If the road is wet enough, that it's covered by water, then the surface makes specular reflections.

Since the vehicle runs on the road, we can collect the reflection strength from different angle in the time domain. If the reflection strength changes due to the angular change, the surface has specular reflection. On the other hand, if it doesn't change, it can have 2 possibilities. First is that it has no specular attribute. Second is the incident light did not change.

2.2 Incident light

The classification between the dry area and the area which doesn't have enough change in the incident light requires the observation of the incident light.

If the camera is heading along the direction of the vehicle, both road and the environment must be captured in 1 image. If the distance between the camera

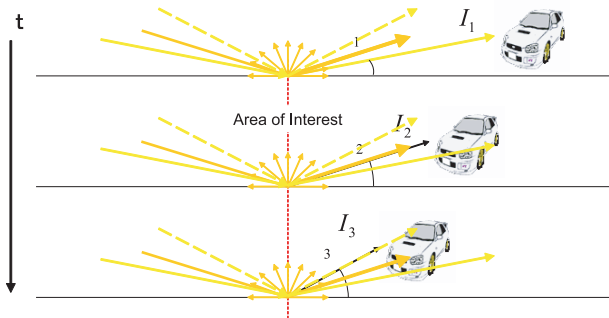


Figure 1: Draft image of the specular reflection and the random reflection

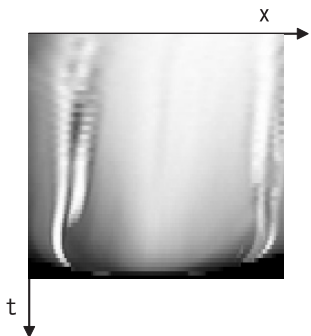


Figure 2: Spatial temporal image

and the environment objects are known, The position where the incident lights come from can be computed.

In sec. 3.2, we explain about the incident light computation. In this paper, instead of estimating the environmental shape, we assume that shape can be modeled by 3 planes.

3 Method

Proposed method is composed by 3 steps. First step tracks the points on the road to create a spatial temporal image. The second step is the computation of the feature from the spatial temporal image. The third step is the classification using 3 features.

3.1 Tracking

A video sequence can be expressed as a 3 dimensional set of pixel expressed by x , y and t . In this paper, x and y express the 2 axes of the image and t expresses the time domain, respectively. On the other hand, the spatial temporal image is expressed by x and t as shown in Fig. 2. Each column express the same place.

3.2 Observation of the incident lights

In this method, we need to compare the incident light and the reflection light among several frames. In this paper, we do not estimate the 3D environmental shape. We assume that the 3D shape are given.

In this section, we explain how to observe the incident light from a single camera with the shape information. For example we explain a situation which

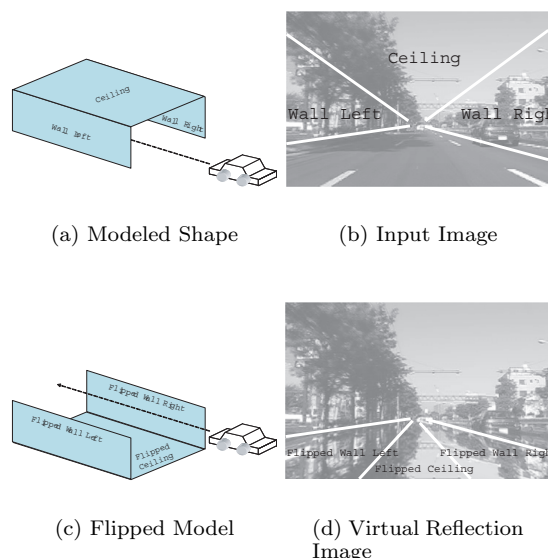


Figure 3: Input image and the incident light

can be expressed with 3 planes. First, each plane is projected in the input image by the known camera parameters (Fig. 3(b)). Each model's corresponding area in the image is preserved as a texture. Next, each plane is flipped against the ground and again projected to the image as shown in Fig. 3 (c). On the image, texture mapping is done to the flipped model's corresponding area by the preserved texture. Then the image appears that the entire ground is made by a specular reflection material. We call this image "Virtual Reflection Image".

In Sec. 3.1, we tracked the pixel of the input image and made the spatial temporal image of the reflection light. By tracking the pixel of the virtual reflection image, we can have the spatial temporal image of the incident light.

To assume the environmental shape as a plane, distance between the camera and the environment object is required to be long enough.

3.3 Computation of the Features

After the tracking, spatial temporal image of both reflection and the incident light are obtained. In these images, each column expresses the 1D temporal signal of the reflection on the same position and the corresponding incident light. For each signal, 3 types of feature value are computed. The norm of the reflection light, norm of the incident light and the inner product of the incident light and the reflection light.

The inner product stands for the similarity measure of the incident light and the reflection light. The reflection light is any time equal to the incident light if the specular reflection has occurred. The calculation of the inner product is done after the subtraction of the average among the time domain.

The norm of the incident light and the reflection light stands for the reliability of the similarity. If the incident light and the reflection light do not change among the time domain, the inner product value become high independently from the surface situation. To avoid the miss detection of such situation, we calculate the norm of the incident and the reflection light.

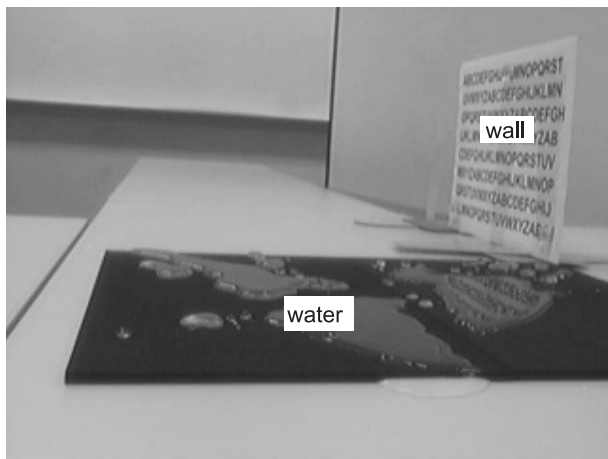


Figure 4: Experiment configuration

3.4 Classification of the area

After sec.3.3, 3 features are calculated from every column in the time space image. Again, a single column in time space image corresponds to a unique position in the real world. To classify each column to wet or dry, we use a nearest neighbour algorithm with a training data. We prepare some training data for the classification previously. From the training data, we calculate the covariance matrix and the average vector. The mahalanobis distance between each feature and the training data are calculated and each result belongs to the nearest class, wet or dry.

4 Experiments

Experiments have been done with both wet road and the dry road to demonstrate the efficiency of our method.

4.1 Experiment on the desk

The experiment has been done at indoor situation to check the reliability of the proposed method. As shown in Fig.4, the water is placed on a black sponge cloth. The black sponge stands for the dry road and makes a random reflection. To make a reflection on the wet surface, a wall with letters was placed next to the road.

The training data was made from the input images.

The Fig.6 shows result and time space images made in this experiment. Figure 6 (a) shows the top view image used for the experiment, (b) shows the manually made correct wet area, (c) and (d) show the time space image of the reflection light and the incident light and (e) and (f) show the detected wet area and dry area.

The precision rate was 81.1% and the recall rate was 34.1%. The main reason for the miss detection is some region did not have the change of the reflection. The black area in the Fig.6(e) corresponds to the wrong detection. That area didn't have the change of the intensity. Thus, the classification went wrong.

4.2 Experiments at outside

Another experiment has been done at outdoor situation. The input images are shown in Fig.7. A puddle

was prepared on the planar. The geometric relationship was measured previously to create an virtual reflection images. The training data was taken from the input images.

The Fig.6 shows result and time space images made in this experiment. Figure 6 (a) shows the top view image used for the experiment, (b) shows the manually made correct wet area, (c) and (d) show the time space image of the reflection light and the incident light and (e) and (f) show the detected wet area and dry area.

The detection rate was 44.3% and the recall rate was 95.0%. The recall rate was high. This means that if the incident light changes, we can detect the wet area. The low detection rate is due to the misalignment of the pixels in the time space image. This causes the change of the intensity though the actual intensity never changed and conclude in the wrong classification. The method depends on the accurate registration of the top-view images.

5 Conclusion

In this paper, we propose a method which detects the wet area on the road surface based on the analysis of the time space image.

The reconstruction of the input images are not explained in this paper. The classification was done by the mahalanobis distance with some training data.

The detection rate of the wet area at outdoor was 44.3% and the recall rate was 95.0%. All computation was done by a single camera.

References

- [1] C. Shannon, "A Mathematical Theory of Communication," *Bell System Technical Journal*, Vol. 27, pp. 379–423 and 623–656, 1948.
- [2] M. Yamada, K. Ueda, I. Horiba and N. Sugie, "Discrimination of the road condition toward understanding of vehicle driving environments" *IEEE Transactions on Intelligent Transportation Systems*, Vol. 2, No. 1, pp. 26–31, Mar 2001.
- [3] Hiroshi Fukui, Junichi Takagi, Yoshiro Murata and Masashi Takeuchi, "An Image Processing Method To Detect Road Surface Condition Using Optical Spatial Frequency", *IEEE Conference on Intelligent Transportation System*, pp. 1005–1009, 1997.
- [4] D. Miyazaki, K. Ikeuchi, "Inverse Polarization Ray-tracing: Estimating Surface Shape of Transparent Objects", *Proceedings of International Conference on Computer Vision and Pattern Recognition (CVPR2005)*, pp.II:910–917, San Diego, CA USA, Jun. 2005.
- [5] Y. Tsin, S. B. Kang, R. Szeliski, "Stereo Matching with Linear Superposition of Layers", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 28, No. 2, pp. 290–301, Feb. 2006.
- [6] Tomoaki Teshima, Hideo Saito, Shinji Ozawa, Keiichi Yamamoto, Toru Ihara, "Vehicle Lateral Position Estimation Method Based on Matching of Top-View Images", *The 18th International Conference on Pattern Recognition 2006*, pp. 626–629, Aug. 2006.

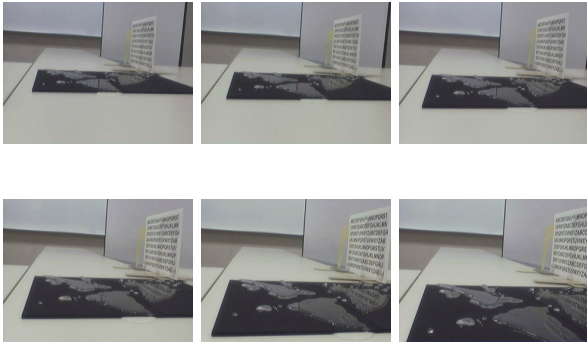


Figure 5: Input images of the experiment

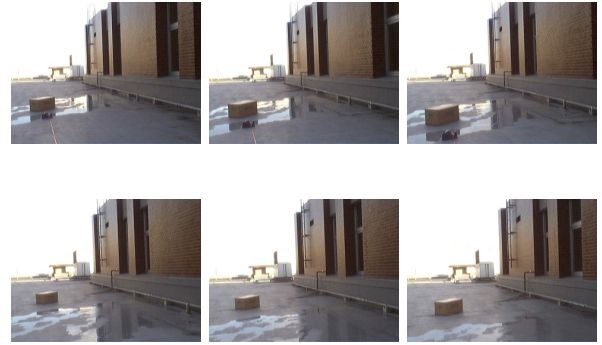


Figure 7: Input images of the experiment at outdoor



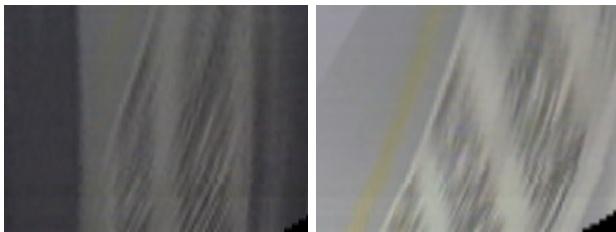
(a) Top-view image

(b) Correct wet area



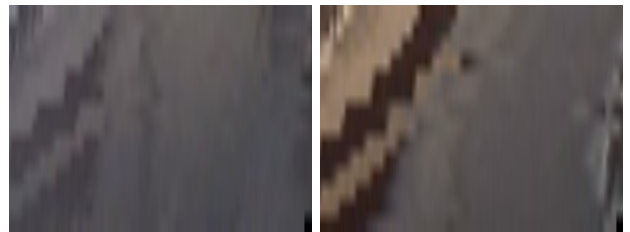
(a) Top-view image

(b) Correct wet area



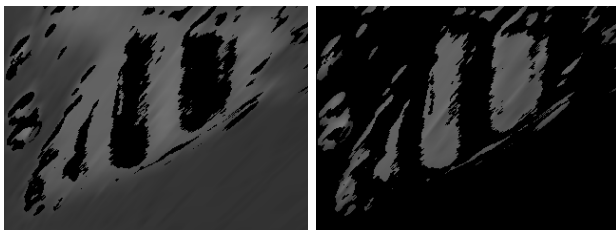
(c) Time space image of reflect light

(d) Time space image of incident light



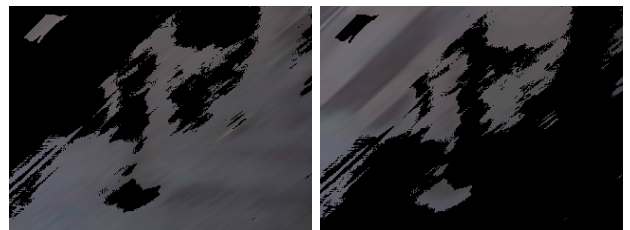
(c) Time space image of reflect light

(d) Time space image of incident light



(e) Deteceted dry area

(f) Deteceted wet area



(e) Deteceted dry area

(f) Deteceted wet area

Figure 6: Result of the experiment on the desk

Figure 8: Result of the experiment at outdoor