APPLICATION OF PATTERN RECOGNITION TECHNIQUES FOR *ITS*

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ABSTRACT

In this paper, we introduce some of our works containing the latest achievements in recognition of large quantities of stored video and low-quality images to support and expand human visual capabilities in the context of driving. We have applied the works to ITS technologies, especially driver-assistance and navigation systems that recognize driving environments with an in-vehicle camera and/or other sensors.

1. INTRODUCTION

Recent years have seen great advances in the development of ITS (Intelligent Transport Systems) technology. For example, driver assistance and navigation with the aid of computers and various sensors are being actively developed. In particular, in-vehicle camera images are commonly utilized, since they contain important visual information. To support and expand human visual capabilities, we have been developing various pattern recognition techniques for large amounts of stored video and low-quality images. We have also been developing applications for ITS recognition techniques as outlined below.

- Enhancement of car navigation systems
  - **Change detection in streetscapes from GPS coordinated omni-directional image sequences** [1] (Section 2)
  - Estimating car location by corresponding series of multiple laser radar data [2]
  - Confirming the existence of stores on an urban map by detecting strip-like signboards [3]
- Weather recognition for driver assistance
  - **Raindrop detection from in-vehicle video camera images for rainfall judgment** [4, 5] (Section 3)
  - **Visibility estimation in foggy conditions by in-vehicle camera and radar** [6] (Section 4)
- Traffic sign and signal recognition
  - Identification of degraded symbols on traffic sign by a generative learning method [7]
  - Recognition of traffic signals in various conditions for safe driving assistance [8]

In this paper, we introduce the works highlighted in bold-face.

2. CHANGE DETECTION IN STREETSCAPES

One aspect of desired ITS technology is to enhance car navigation systems in terms of offering better information to drivers. In these systems, navigation maps are important. However, these need frequent updates because of streetscape changes such as road works and new buildings. Updating a map, however, is expensive, since many people have to actually walk through the city and collect a lot of relevant information.

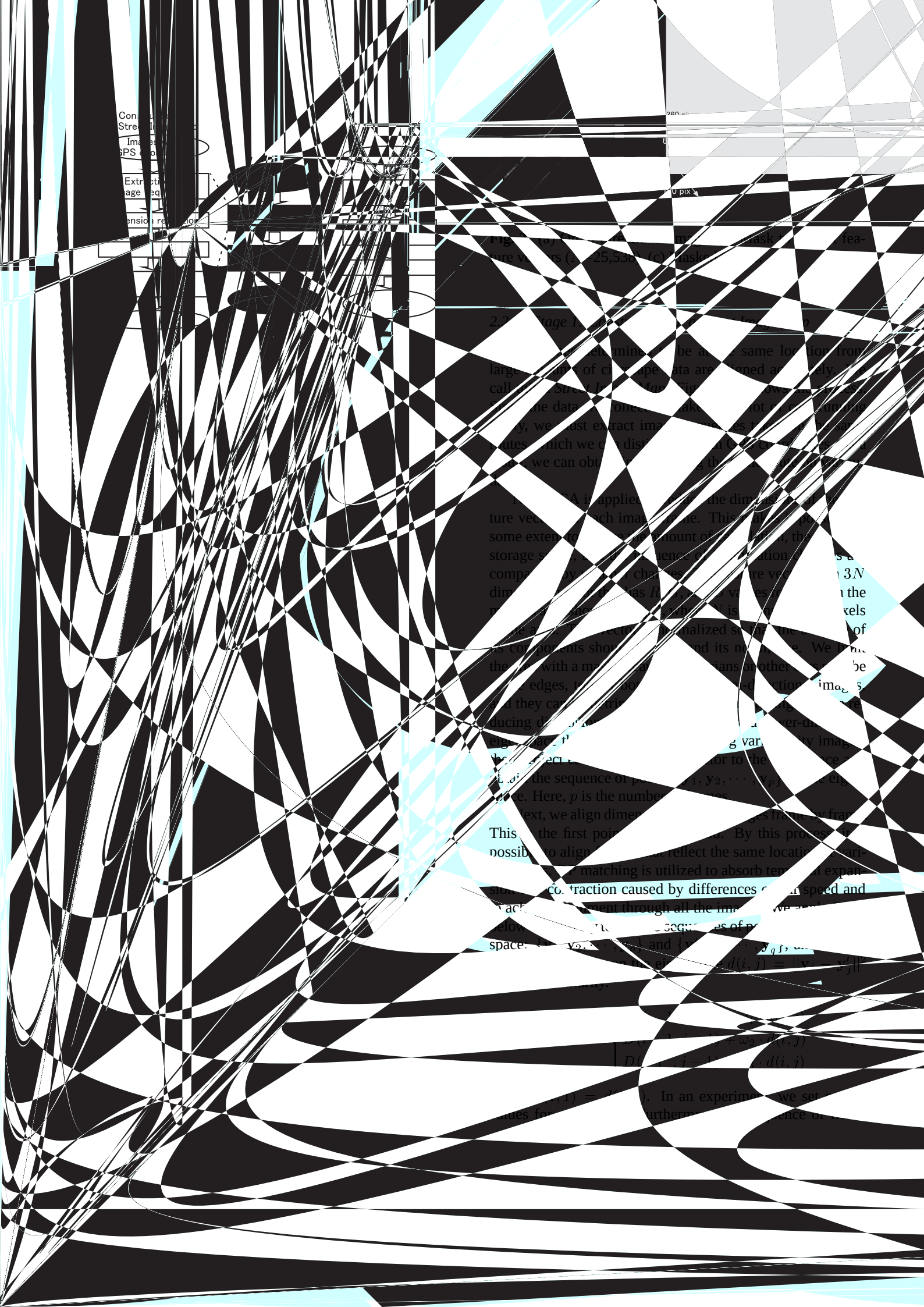
2.1. Approach

For quick and efficient updating of maps, we have developed a method of automatically detecting changes in streetscapes from omni-directional images taken from cars.

In collecting street image data, we assume that many cars with general GPS and an omni-directional camera run freely without purposefully collecting the data. Consequently, we can obtain a large amount of GPS-coordinated images taken at various times and routes with a low-cost system. We use an omni-directional camera to efficiently capture images in all directions from the cars. To collect position information, high-accuracy GPS such as RTK GPS may be available, but it does not suit our application because of its cost. Therefore, we assume the use of a general GPS or D-GPS fitted to conventional car navigation systems. Such GPS, however, has an approximately 10-m margin of error, meaning that we cannot correctly gather images at identical locations by simply collecting images that have the same coordinates.

For the reasons mentioned above, we need to solve the following three problems.

1. Accurate alignment of images of the same location from images collected by freely running cars at various times.



number pairs (i, j) chosen up to $D(p, q)$ have been calculated to show matches of two image frames.

The second point of our method is to average GPS coordinates attached to the aligned images with the aim of obtaining accurate position information. It is known that the average of the coordinates measured at a particular location for a long time converges at the true coordinates. Based on this, it is considered that the average coordinates are more accurate than the collected data.

2.2.3. *Stage 2: Detection of changes*

It is the third point of our method to detect changes in streetscapes from images of a specified location aligned in the first stage. Figure 1(c) shows this process.

The aligned frames of the specified location are sorted in order of time, namely, P_0, P_1, P_2, ... The dissimilarity between P_0 and the other frames P_i $(i = 1, 2, \ldots)$ is calculated by approximately adjusting their positions to reduce the influence of the car's position in the lane. If their variance exceeds a threshold d_T, we determine that there is a change, but if the camera catches a reflection off a large car or if image alignment fails at certain frames, the dissimilarity will rise temporarily. Therefore we restrain it from temporarily rising by median-filter and Gaussian-filter smoothing over the time sequence of the dissimilarities.

2.3. Results and discussion

2.3.1. *Stage 1: Construction of a Street Image Map*

First, we experimented on the construction of a *Street Image Map*, confirming the accuracy of image alignment. We used 44 data items collected over about a year, and aligned the oldest data with the other data. For the alignment, we extracted a route of about 170 m from the data, and reduced the 64,458 dimensions of the feature vectors to 20 dimensions. In terms of DP matching, the weight factor $(\omega_1, \omega_2, \omega_3)$ is $(2, 1, 2)$ from Eq. 1. This was the best weight in the pilot study.

We judged the results by manual checking. If a frame was aligned to its most similar frame, we judged it to be correct, while if there were some frames more similar than it, we judged it as false. We evaluated the rate of correctly aligned frames in all frames, which resulted in an average of 94.1%. Figure 3 shows a part of frames aligned at a certain location on the route. Their standard deviation of the GPS coordinates attached to the correctly aligned frames at that location was 6.86 m, which is assumed to be the accuracy of the GPS coordinates for measurement over a long time. The average of these standard deviations over all frames was 7.98 m. The data were collected at speeds under 40 km/h, and the frame rate was 30 fps, so the distance between the locations of two consecutive frames was less than 0.4 m. Thus the average coordinate has a 0.4 m margin of error in the car's direction of travel even if the alignment is correct and the position information is accurate. Therefore, it is assumed that if the number of samples increases, we can converge the error of position information to about 0.4 m in the direction of travel.

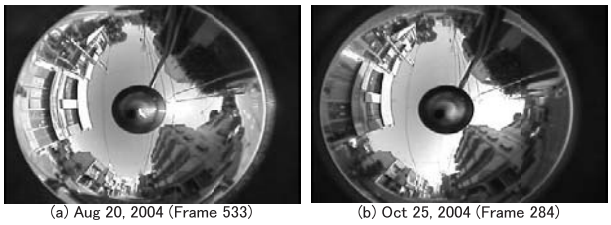


Fig. 3. Example of aligned frames.

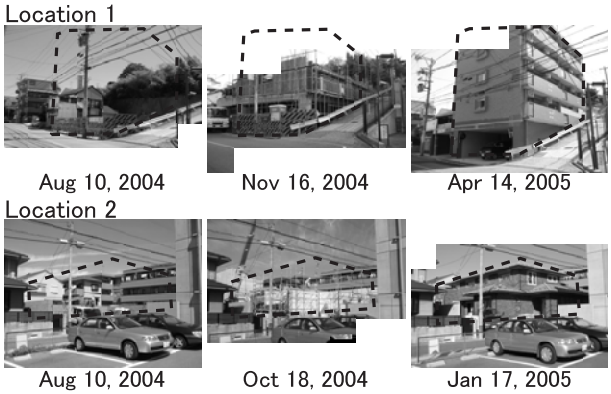


Fig. 4. Example of images at change-detected locations: The area where the streetscape changed significantly is marked by dashed lines.

2.3.2. *Stage 2: Detection of changes*

We also experimented on detection of changes using the same data used in Section 2.3.1. This time there were four extracted routes, which included four major changes in the streetscapes. Threshold d_T was set experimentally.

According to the results, we correctly detected three changes out of four. Figure 4 shows images of the detected locations. These images reveal that there were indeed changes at the detected locations. For the remaining case, where the change was too small even from human eyes, our method could not distinguish a sufficiently large dissimilarity.

2.4. Conclusion

We have developed a new method that detects changes in streetscapes from many street images taken at various times. Experiments produced the following three results.

- Images were aligned with a high accuracy of 94.1%. It is, therefore, possible to align images taken at the same

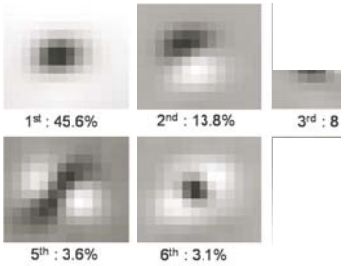


Fig. 7. Eigendrops and their contribution rates.

3.2.2. *Learning Stage*

First, a rectangular region circumscribing each raindrop is cut manually as a training set from images of a windshield taken in rainy weather. A total of *K* images is 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 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 are called "eigendrops."

3.2.3. *Detection Stage*

Raindrops are detected from the test images as follows. First, to emphasize the image features of raindrops, an averaged image is produced from multiple sequential frames obtained from the input video. In the averaged 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 $S(\mathbf{a})$ of $\mathbf{a}$ 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. The coordinates 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 of the raindrop candidates.

3.2.4. *Judgment Stage*

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

3.3. Experiments

3.3.1. *Setup*

We mounted a digital video camera in a car and took the images (30 fps, 640×480 pixels, grayscale). Our method was applied to each frame of the input video sequence. Then the recall and precision ratios for raindrop detection were calculated to evaluate the detection accuracy. In the learning stage, the eigendrops were made from 500 raindrop images. Figure 7 shows eigendrops created from the clipped raindrops. The subspace dimension was six when the eigendrops were made.

3.3.2. *Results*

Figure 8 shows examples of raindrop detection in some experimental conditions, while Fig. 9 illustrates the recall and precision curves. It is clear that when the number of frames used for averaging increases, although recall improves significantly, precision drops somewhat. Furthermore, when the number of frames used for frame-matching increases, although precision improves, recall falls. The best result was precision of 0.97 and recall of 0.51 when the similarity threshold was 0.70 under five-frame averaging and ten-frame matching.

3.3.3. *Discussion*

Precision is more important than recall in practice for a windshield wiper controller, since to incorrectly recognize raindrops and let the windshield wiper malfunction must be avoided. However, it is also a problem when recall is too low. While this result was obtained from the entire image, it was not inferior to the result obtained by our previous method that restricted the target region of raindrop detection to the sky region (precision = 0.97, recall = 0.59).

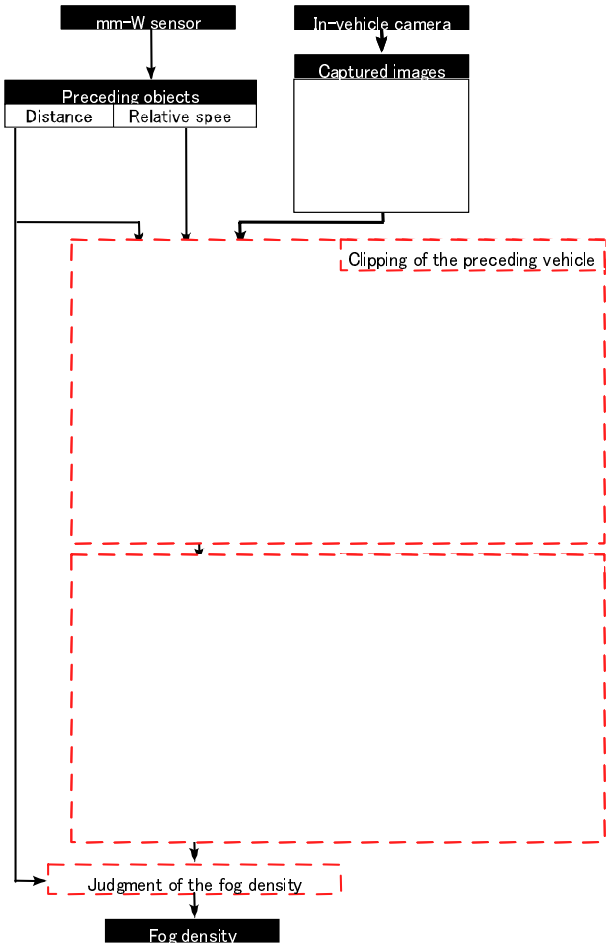
Since the success rate of rainfall judgment using the result of raindrop detection from the sky region showed 89%, the new method should also be able to judge rainfall similarly.

3.4. Conclusion

We have been developed a new method that detects raindrops in background areas using inter-frame information. Experimental results illustrated the method's effectiveness as follows:

- Our method could detect raindrops from an entire image with high accuracy (97% precision and 51% recall) that was almost the same as that of the previous method using only sky regions.
- The success rate of rainfall judgment using the result of our method is considered to be up to 89%.

In future, we will evaluate the method under various rainy weather situations according to time, place, and rainfall.


mm-W sensor
In-vehicle camera
Captured images
Preceding objects
Distance
Relative spee
Clipping of the preceding vehicle
Judgment of the fog density
Fog density

driving a vehicle. Five sets of images were tested, where one set included ten images that had been selected randomly from the captured ones. Four different subjects, each with a valid driver's license, participated in the experiment. They classified the ten images into three classes for each set, and from the result of this experiment, we obtained the appropriate class for each image, which complies with human perception.

4.3.2. Evaluation method

We compared the judgments by our method and those by human subjects. In the following experiments, the test data set was different from the training data set. The preceding vehicle was always the same vehicle in the experiment and the sky luminance was almost the same when the images were captured. Assuming that L_0 and L_f in Eq. 2 are invariables from this, the regression curve was calculated for each class.

4.3.3. Results and Discussion

The results presented in Table 1 show the confusion matrix for judgment by the proposed method and that by the human subjects. The total precision rate for all classes was 85%. In the experiment, we dealt with only one vehicle. In reality, however, the indicator is affected by the variety in color or shape of vehicles, though the indicator should not be affected by these variances for reliable judgment of fog density. Thus, improvement of the indicator is our next challenge.

4.4. Conclusion

We have developed a method that classifies fog density according to a visibility feature of a preceding vehicle and the distance to the vehicle. We obtained promising results (85% of precision) through an experiment using data collected from an in-vehicle camera while driving a vehicle. From the results, we confirmed that the proposed method can make judgments that comply with human perception.

In future, we will consider an improved visibility feature that does not vary depending on the type or color of a preceding vehicle. In addition, we will consider a situation where there is no preceding vehicle at all.

5. SUMMARY

In this paper, we have briefly introduced three works related to application of pattern recognition for ITS. Future work will involve conducting research on recognition and understanding of video and images. For more details of our works, please visit our website *http://www.murase.m.is.nagoya-u.ac.jp/*.

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The works are developed based on MIST library, available at *http://mist.suenaga.m.is.nagoya-u.ac.jp/*.

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