Environment Adaptive Pedestrian Detection using In-vehicle Camera and GPS

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Abstract: In recent years, accurate pedestrian detection from in-vehicle camera images is focused to develop a safety driving assistance system. Currently, successful methods are based on statistical learning. However, in such methods, it is necessary to prepare a large amount of training images. Thus, the decrease in the number of training images degrades the detection accuracy. That is, in driving environments with few or no training images, it is difficult to detect pedestrians accurately. Therefore, we propose an approach that collects training images automatically to build classifiers for various driving environments. This is expected to realize highly accurate pedestrian detection by using an appropriate classifier corresponding to the current location. The proposed method consists of three steps; Classification of driving scenes, collection of non-pedestrian images and training of classifiers for each scene class, and associating a scene-class-specific classifier with GPS location information. Through experiments, we confirmed the effectiveness of the method compared to baseline methods.

1 INTRODUCTION

In recent years, traffic accidents involving pedestrians are becoming a social problem. Therefore, assistance technology for safety-driving is necessary, such as warning of the existence of pedestrians. Additionally, driverless vehicles are expected to be upcoming in the near future, due to the recent evolution of automatic driving technology. Pedestrian detection is one of the key function to develop these systems. To tackle this problem, various methods have been proposed using in-vehicle camera images.

For example, Dalal et al. developed a method for pedestrian detection that combines the Histograms of Oriented Gradients (HOG) feature and the Support Vector Machine (SVM) classifier (Dalal and Triggs, 2005). In the case of such a statistical learning approach, a large number of training images is needed for accurate detection. Thus, the decrease of the number of training images degrades the detection accuracy. In driving environments with few or no training images, it is difficult to detect pedestrians accurately.

Some methods achieve highly accurate pedestrian detection by restricting its application to a specific environment so as to make use of particular knowledge (Broggi et al., 2009) (Vinicius et al., 2012), but such an approach is not sufficient to detect pedestrians from an in-vehicle camera, since driving environment varies widely such as the examples shown in Figure 1.

Figure 1: Examples of various environments. It is difficult to detect pedestrians accurately for all environments with a general detector.

To solve this problem, some research groups proposed methods that collect training images of pedestrians automatically from videos. For stationary cameras, there are methods based on background subtrac-

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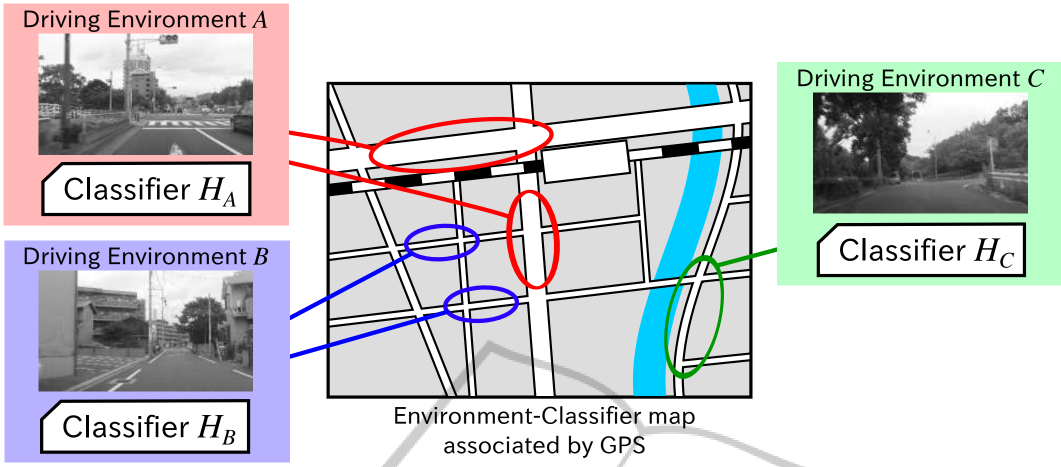


Figure 2: The concept of the pedestrian detector adapted to the driving environment.

tion for collecting pedestrian images (Nair and Clark, 2004) (Wang and Wang, 2011). However, it is difficult to apply techniques used in these methods for in-vehicle camera videos. Wöhler et al. solved this problem by employing tracking (Wöhler, 2002).

The above methods construct a single classifier to detect pedestrians from all environments. On the other hand, some methods take a transfer learning approach to change the performance of the classifier for each environment (Pang et al., 2011). However, to apply these methods, it is required to prepare training samples obtained from each environment manually.

Therefore, we take an approach that collects training images automatically to build classifiers for various driving environments. By choosing an optimal classifier for the current environment, accurate detection is expected. We call this approach as "driving environment adaptation."

A driving environment affects the appearance of pedestrians and their background, which decreases the detection accuracy. Factors blamed for this effect are:

- The location changes the background appearance.
- The time affects the illumination of the driving scene.
- Weather conditions and seasons affect the appearance of pedestrians and backgrounds.

Compared to the effect of time, weather conditions and seasons, the effect of location is more significant. It is difficult to prepare training images manually considering the variation of all locations. For this reason, adapting the pedestrian detector to location should be effective. Figure 2 shows the concept of the pedestrian detector adapted to the location.

When building a classifier, pedestrian and non-pedestrian images are required. In addition, appearance of the non-pedestrian (background) image changes significantly according to the location. On the other hand, the variety of appearance of pedestrians is not so large compared with the non-pedestrian images. Hence, this paper focuses on the collection of non-pedestrian images.

The proposed method is composed of the following parts:

1. Classification of driving scenes
2. Collection of non-pedestrian images for each scene class
3. Associating a scene-class-specific classifier with GPS location information

The main contribution of this paper is the introduction of the concept of an environment adaptive detection mechanism for pedestrian detection from in-vehicle camera images. This framework can be combined with any conventional learning-based pedestrian detection methods.

In the following, section 2 explains the details of the proposed method. Section 3 describes the experiments. The results of the experiments are discussed in section 4. Finally, we conclude this paper in section 5.

2 BUILDING A PEDESTRIAN DETECTOR ADAPTED TO THE DRIVING ENVIRONMENT

This section describes the details of the proposed method.

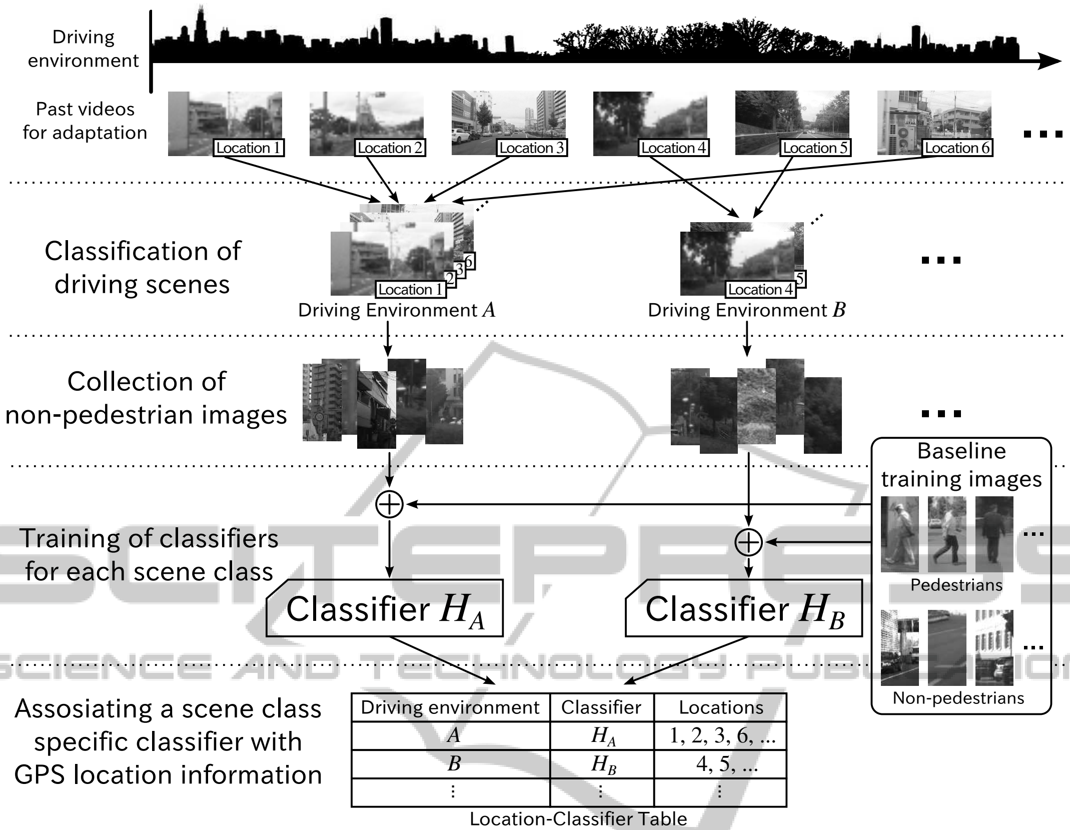


Figure 3: The proposed framework of adapting a pedestrian detector to driving environments using in-vehicle camera videos captured multiple times along the same route.

2.1 Overview of the Proposed Method

The proposed method consists of two phases; the adaptation phase and the detection phase.

The adaptation phase is the process that constructs a pedestrian detector adapted to a location. Figure 3 shows the framework of the adaptation phase. First, the proposed method classifies driving scenes based on the appearance, and then automatically collects non-pedestrian images from in-vehicle camera videos corresponding to each scene class. Finally, the classifier is adapted to the environment by using training images obtained in each scene class. Since a geographic location can be obtained from GPS, the classifiers adapted to each driving scene class is associated with GPS location information. This relation is represented as a "location-classifier table."

The detection phase is the process that detects pedestrians using a classifier adapted to the current driving scene class. Such a classifier is obtained by looking-up the location table referring to the current location obtained by GPS.

Since we suppose that the appearance of the same region should be similar regardless of the direction of the car, the differences of orientations are not considered.

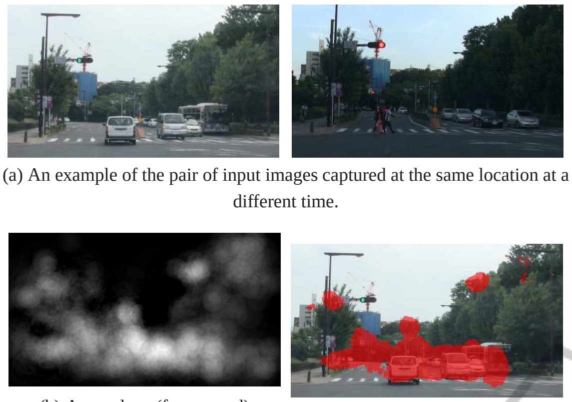
The following sections describe the details of each process.

2.2 Adaptation Phase

2.2.1 Classification of Driving Scenes

The proposed method classifies driving scenes using in-vehicle camera videos captured multiple times along the same route. In this process, Bags of Visual Words (BoVW) (Csurka et al., 2004) based on the Speeded Up Robust Features (SURF) feature descriptor (Bay et al., 2008) are extracted for each frame as the driving scene feature descriptor. Then, driving scenes are classified by k-means clustering using the scene features. Here, the parameter k indicates the number of driving scene classes.

In the following, we used 100 bins for the BoVW codebook. That is, driving scene features are represented by a 100-dimensional vector.



(a) An example of the pair of input images captured at the same location at a different time.

(b) Anomalous (foreground) likelihood map.

(c) Anomalous region detected by thresholding the likelihood map.

Figure 4: The input images and the result of anomalous region detection.

2.2.2 Collection of Non-pedestrian Images and Training of Classifiers for each Scene Class

After the classification of driving scenes, to obtain classifiers adapted to a scene class, the proposed method collects non-pedestrian images automatically from corresponding in-vehicle camera videos. Training images are collected by clipping images randomly that contain no pedestrian. To achieve this, the proposed method detects anomalous regions from two images taken at the same location at a different time, based on the ideas of local feature correspondence-based change detection (Sand and Teller, 2004) (Mitsumori et al., 2009).

First, the two images are aligned by calculating the homographic transformation based on local feature correspondences. Then, local features are extracted, and their correspondences between the aligned images are calculated again. The existence of corresponding keypoints between regions indicates their similarity. Conversely, regions with miss-correspondences or no correspondence are considered as anomalous. Through this process, an anomalous (foreground) likelihood map is obtained. By thresholding this likelihood map, anomalous regions are detected.

Figure 4 shows the result of the anomalous region detection. We can see that the method can extract differences between the images caused by vehicles and pedestrians robustly against illumination variations and small misalignments.

Collecting non-pedestrian images is the process that clips images randomly from outside the anomalous regions. Images clipped by this process are assumed not to include any pedestrian. Through this process, images for the negative samples, that are expected not to include pedestrians, are obtained. By learning the collected images and manually prepared images, a classifier adapted to a scene class is obtained.

2.2.3 Associating a Scene Class Specific Classifier with GPS Location Information

By referring to GPS location information associated with each frame, the relationship between locations and driving scene classes is obtained. This relationship is represented by a table. In this table, the keys to look up for a classifier associated with a scene class are multiple GPS locations. This concept can be considered that each location is linked with an optimal classifier, such as shown in the example illustrated in Figure 2.

2.3 Detection Phase

In the detection phase, the proposed method selects a classifier adapted to the current location associated with the input image, which should be the optimal. This is performed by referring to the location-classifier table using GPS location information as a key. Since classifiers are sparsely associated with the table, the proposed method searches for a classifier by the *k*-nearest neighbor scheme. Since the additional computation introduced in the detection phase compared with a general pedestrian detection scheme is just selecting a classifier, this method is practical enough for real-time processing.

3 EXPERIMENTS

We conducted experiments to evaluate the effectiveness of the proposed method. This section introduces the dataset, the comparative methods, and the evaluation method.

3.1 Dataset

We prepared a dataset composed of in-vehicle camera videos with frame-wise GPS location information that were captured multiple times along the same route. This data consists of three sequences of in-vehicle camera videos which have GPS location information for each frame. They were captured along the same route at a different day, time and weather conditions. Each video had a resolution of 1,920×1,080 pixels with 28 mm focal length, recorded in 24 fps progressive mode.

Table 1: Specification of the dataset.

Sequence	Travel length	Video length	Weather	Time
Evaluation	7 km	23 min.	Cloudy	Daytime
Training 1		35 min.	Fine	Sunset
Training 2		28 min.	Rain	Sunset

(a) An example of the training sequence 1

(b) An example of the training sequence 2

(c) An example of the evaluation sequence

Figure 5: Examples of in-vehicle camera images used in the experiments. These images were taken in the same location under different conditions.

Table 2: The outline of the methods (the number of training images).

Method	Manual preparation		Automatic collection		Total		Environment adaptive
	Positives	Negatives	Positives	Negatives	Positives	Negatives	
Baseline	4,104	5,000	–	–	4,104	5,000	–
Comparative 1	4,104	10,000	–	–	4,104	10,000	–
Comparative 2	4,104	5,000	–	5,000	4,104	10,000	–
Proposed	4,104	5,000	–	5,000	4,104	10,000	✓

The route contained main roads, residential areas, and suburbs. Table 1 shows the specifications of each video, and Figure 5 shows examples from each video. We used two sequences for the training, and the remaining sequence for the evaluation.

Additionally, training images for building a pre-adaptation classifier were prepared manually. These were collected from images taken in an area different from the experimental data.

3.2 Comparative Methods

Table 2 shows the outline of the methods. The proposed method is the environment adaptive detection that combines the driving scene classification and the automatic training image collection. The baseline method used the pre-adaptation detector built only with manually prepared training images. Comparative method 1 increased the number of training images of the baseline method, without collecting training images automatically and driving scene classification. Comparative method 2 used the detector adapted to the whole training video without driving scene classification, that is equivalent to the case of the proposed method supposing if the number of scene classes were 1. The same number of training images was used in the proposed method and the comparative methods.

3.3 Evaluation

In the pedestrian detection experiment, we focused on pedestrians that had a height of 192 pixels or more in the image, without large occlusion. The evaluation sequence contained a total of 372 pedestrians.

To detect pedestrians from an input image, multi-scale window search was conducted. Detection windows were fully raster-scanned over the image, and detection score was calculated by a classifier from the feature of the clipped window. Detection windows whose score was above the detection threshold were regarded as pedestrians. Through this process with changing the scale of input image, various sized pedestrians could be detected. The detection result was considered to be a true positive if the overlap of the rectangles with the ground truth reached 30%. In order to prevent false positives, it is effective to introduce some hypotheses on the position of pedestrians. However, since we attempted to validate only the accuracy of the classifier, this experiment was conducted without such schemes.

To build the classifier, any conventional learning-based method can be used in the proposed method. In this experiment, the HOG feature and the soft-margin linear SVM implemented in LIBLINEAR (Fan et al., 2008) were used.

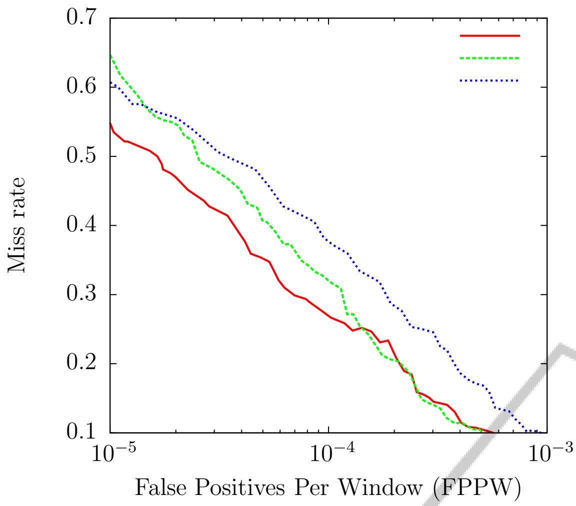
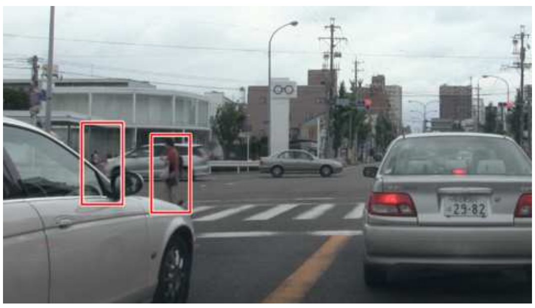


Figure 6: The result of the accuracy evaluation of environment adaptive pedestrian detection (when the number of driving scene classifier was $k = 10$).

(a) Location adapted detector.



(b) Baseline detector.

Figure 7: Example 1 of the detection result of the proposed method and the baseline method.

Here, we plot the detection-error-tradeoff (DET) curve by changing the detection threshold to evaluate the detection accuracy, whose horizontal axis represents the number of false positives per window (FPPW), and the vertical axis the miss rate (undetected rate). So, a curve closer to the origin indicates that it is more accurate. This graph is drawn by plotting the evaluation results by changing the parameter of the SVM classifier.

4 RESULTS AND DISCUSSIONS

This section shows the results of the experiment. In the following, we first evaluate the general performance, and next detailed analyses of how the proposed method works.

4.1 Evaluation of the Accuracy of the Pedestrian Detector adapted to Driving Environment

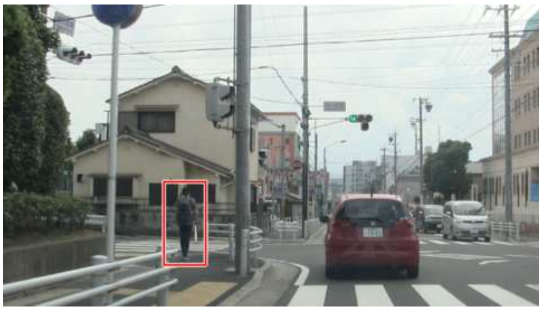
Figure 6 shows the results of each method. We can see that the environment adapted pedestrian detector was the most accurate compared with all the other methods. As seen in the comparative methods 1 and 2, collection of training images from actual video was much effective than simply increasing the number of training images. Furthermore, the result of the proposed method indicates that using location dependent classifiers was more successful. Especially when FPPW $= 10^{-4}$, the miss rate of the proposed method decreased 28% compared with the baseline. Also in comparison with the comparative methods, the proposed method was the most accurate in most cases.

As shown in Figs. 7 and 8, that are examples of the detection result of the baseline method and the proposed method, adaptation of pedestrian detectors to the environment decreased the number of miss-detection.

However, miss-detection was frequently observed in vehicle regions such as those shown in Figure 9. In the proposed method, the collected images will not include any vehicle region that can be used as negative samples. Thus, when collecting non-pedestrian images, it is desirable to collect such regions to prevent such miss-detection. However, since the proposed method is based on image difference, it is not possible to extract only pedestrian regions precisely. Solution to this problem will be considered in the future.

4.2 Investigation of the Relation between the Number of Driving Scene Classes and the Detection Accuracy

In the experiment, we had a fixed parameter that represented the number of driving scene classes; k. Figure 10 shows the detection accuracy of the proposed method by changing k. Finer classification makes the accuracy better, but it also increases the size of the classifier pool. Therefore, it is a trade-off



(a) Location adapted detector.

(b) Baseline detector.

Figure 8: Example 2 of the detection result of the proposed method and the baseline method.

Figure 9: An example of miss-detection that could not be eliminated by the proposed method.

between the cost and the accuracy, so we must choose an adequate value for k.

Figure 11 shows examples of the collected non-pedestrian images. Even if the scene is crowded with pedestrians, the proposed method was able to automatically collect non-pedestrian images properly. In order to improve training image collection, a more sophisticated method might be effective instead of random clipping. For example, collecting images close to the road surface, or using miss-classified results (false positives).

Figure 12 shows the result of scene classification

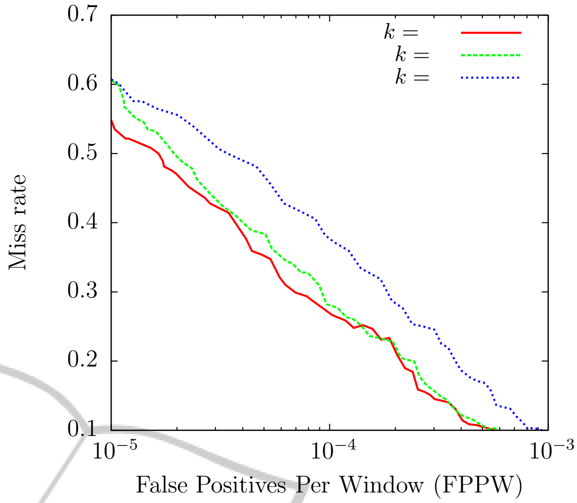


Figure 10: Relationship between the number of driving scene classes k and the detection accuracy. Here, $k = 1$ is equivalent to comparative method 2.

Figure 11: Examples of non-pedestrian training images collected automatically.

mapped using GPS location information. Each color plotted on the road corresponds to a scene class. We can observe that there are some cases that the color changes frequently in a short section. It indicates that the classification results were not stable. This is because the proposed method classified the driving scene for each frame independently. Incorrect classifications were caused by the degradation of the entire image, such as a big motion blur, occlusions by vehicles in front, or over-exposure. To tackle these problems, removing outliers using temporal information might be effective.

5 CONCLUSIONS

In this paper, we introduced the concept of location adaptive pedestrian detection, and proposed a method to create an accurate pedestrian detector adapted to locations. To apply the optimal classifier for a scene class, we built classifiers adaptive to driving environments by collecting scene-wise training images. Through experiments, we confirmed the effectiveness of the proposed method. This framework can be com-

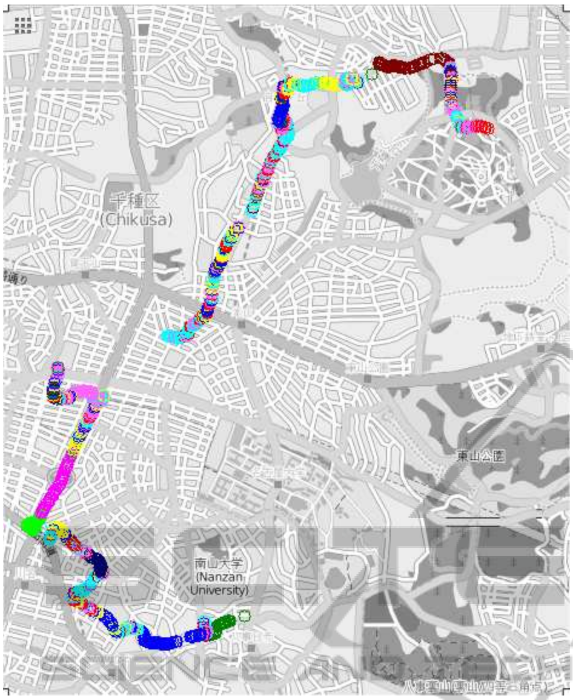


Figure 12: The result of driving scene classification drawn on the map. Each circle with a different color plotted on the road corresponds to a scene class.

bined with any conventional learning based pedestrian detection methods.

For future work, we will extend the method so that it can be adapted to other factors of the driving environment such as time, weather conditions, or season changes. In addition, we will improve the scene classification by replacing the current BoVW and *k*-means scheme, and the training image collection methods.

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