Focusing on Discrimination Between Road Conditions and Weather in Driving Video Analysis

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Abstract. We study an often ignored problem, the discrimination between road conditions and weather in driving videos, which may possibly lead to imperceptible errors on driving data analysis. We explore BDD100K, a common driving video database, and Kyushu Driving Data, a huge driving database created by ourselves. In our experiments, we use road condition labels and weather labels respectively to train several deep models on driving image sequences and demonstrate the difference between the two varieties of labels. The results indicate a significant difference between the two varieties, which leads to different performance of deep models.

Keywords: Driving video · Road condition · Weather classification · Deep learning

1 Introduction

With more and more driving data available since the era of big data began, analysis on driving data has attracted huge attentions. Typically, driving videos contain plentiful and comprehensive information, which can be extracted using modern computer vision approaches.

Usually, when performing analysis on driving, probe data which contains common information such as velocities, GPS positions is the first choice that researchers may consider. With the rapid development of computer vision technology, more and more works start to involve utilization of driving videos and public driving video datasets such as BDD100K [13], which contains various ground truth attributes have been released. Typically, road condition is an important factor which may have huge impact on driving behaviors. For example, a driver who is driving on a wet road may slow down the vehicle. In low visibility conditions such as heavy snow or fog, sudden braking may occur more than in usual clear conditions.

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Confusion of Road Condition and Weather. In fact, the concept of road condition is rarely seen in modern driving video datasets. Instead, "weather" is more commonly presented. Even from a normal person's intuition, it is believed that these two concepts are different, and road condition has more impact on driving behaviors rather than weather. In practical, these two concepts also may have discrimination. For example, after a heavy rain stops, the road may still keep being wet for a period of time. However, we observe that these two concepts are often been confused or the discrimination is often ignored in research. When we try to determine the "weather" from a driving video, we may use the clues of the road condition, the pedestrians who hold up umbrellas, etc., which may lead to confusion of the two concepts. Figure 1 shows an example from BDD100K [13] dataset. Both the images are labeled with weather attribute "rainy", but the left one is exactly the circumstance that the weather is clear but the road is wet.

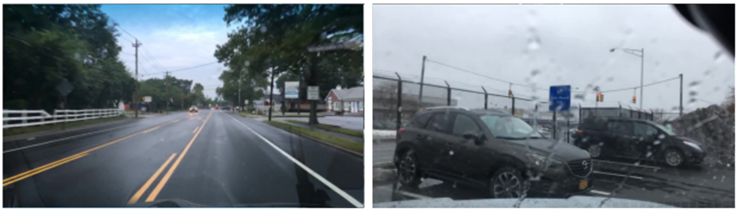


Fig. 1. Two sample images from BDD100K test set. The left one has clear sky but wet road, while the right one is totally rainy. The ground truth weather attributes of the both are "rainy".

In this paper, we tend to raise the concern that when performing driving video analysis, a clear distinguish between "weather" and "road condition" should necessarily be made. To address this issue, we concretely design an application scene, which is performing image classification by a deep neural network. To switch between weather and road condition, we feed the network with differently labeled data. In the following, we first introduce related works (Sect. 2). Then we explain our research process in detailed, including our modified datasets (Sect. 3). In Sect. 4, we show our experimental results with proper analysis. Finally, we conclude our work (Sect. 5).

2 Related Works

In this section, we first introduce works on driving data analysis, followed by an introduction about weather classification from a single image.

2.1 Vehicle Probe Data Analysis

Many works have adopted data mining techniques to analyze vehicle data. He *et al.* [4] uses a mapping-to-cells method to construct a dynamic traffic diagram, and uses it to extract traffic congestion from the probe data. Park *et al.*

[10] proposes a Bayesian structure equation to recognize congestion patterns for road segments. Their work can predict secondary incident occurrences with new information available from the approach, which is significant to traffic accident prevention. As for the sudden braking estimation, Kawatani *et al.* [6] proposes an SVM-based feature selection model to estimate sudden braking.

2.2 Road Condition Analysis

Analysis on road conditions is actually not rare in researches related to transportation systems. Commonly, road conditions refer to whether the road is easy to drive. Several factors such as smoothness, incline may be considered. However, researchers usually use their own concrete aspects of road conditions depending on their different objectives in their works.

Tang *et al.* [11] proposes a new car-following model which considers road conditions. In their work, road conditions are defined as "good" or "bad" according to whether they are easy to drive. Bhoraskar *et al.* [1] develops a traffic and road condition estimation which can estimate road conditions (smooth, bumpy, inclined) and environment conditions (clear sky, covered with trees) with smartphone sensors. Jokela *et al.* [5] proposes a road condition monitoring system with stereo input. Their road conditions refer to ice, water, snow, dry and so on and utilize texture analysis to detect them.

2.3 Weather Classification

Weather classification on images has been widely studied since Convolutional Neural Networks (CNN) have achieved great success on image classifications. Lu *et al.*'s work [9] propose a 2-class classification method which extracts weather cues into features during the training process. They also provide a outdoor weather image dataset consisting of 10K sunny and cloudy images. Elhoseiny *et al.* [2] improves the previous work with a better-designed model, which reached an accuracy of 82.2%. However, in practical the categories of weather are relatively rich. Hence multi-class weather classification is essential for practical usage.

Zhang *et al.* [14] proposes a multi-class weather classification method which aims to 4 categories, sunny, rainy, snowy and haze by extracting corresponding features. They provide another weather classification dataset which contains 20K outdoor images called MWI dataset. Lin *et al.* [8] notice the regional differences of images between different weather. They leverage that information and propose a concurrency model which can classify among sunny, cloudy, rainy, snowy, haze and thunder. They provide a improved dataset called Multi-class Weather Dataset (MWD) which contains 65,000 images. Guerra *et al.* [12] adopt a novel data augmentation technique to improve the classification performance. Their classifier recognizes among sunny, cloudy, rainy, snowy and foggy. Similarly, they provide another dataset called RFS dataset.

The data used in above works usually has clear clues that can indicate the weather. However, driving videos are rarely used for weather classification, which are more difficult because the clues in driving images are not so apparent.

3 Image Classification

3.1 BDD100K Dataset

BDD100K [13] is a large-scale diverse driving video database by University of California, Berkeley, which contains 100k driving images with a variety of attributes such as weather, scene, time of day and 2D bounding boxes. The weather of images is clarified to 6 categories, which are clear, rainy, snowy, partly cloudy, overcast and foggy. We only adopt images during the day. Table 1 shows the quantities of each category.

Table 1. The quantities of each categories in BDD100K after selecting only daytime data.

Weather	Training set	Test set
Clear	12454	1764
Rainy	2522	396
Snowy	2862	422
Overcast	7551	1039
Partly cloudy	4262	638
Foggy	48	5
Total	29699	4264

Since a concrete annotation criteria of weather is not mentioned in [13], we believe that the "weather" in BDD100K may be annotated depending on annotators' judgment when they see the images due to our observation. We consider that the probability which they have referred to meteorological information is low and no strict criteria is made to define the "weather" attribute.

3.2 Kyushu Driving Data

Besides the public BDD100K data, we collect data from drive recorders among 45 vehicles from December 2017 to January 2018 in Kyushu region and Yamaguchi Prefecture, Japan. The total number of recorded hours is roughly 1493, and all the driving videos have a total size of 172 GB. Figure 2 shows some sample images from the driving videos.

Fig. 2. Some examples of our driving video data.

Meteorological Observatories. To leverage pure weather information without any confusion, we exploit weather-related information from 19 meteorological observatories with the frequency of 60 min. The weather categories of observatories are relatively abundant, including "overcast", "rainy", "clear", "sleet", "snowy", "foggy", "sunny", "precipitation", "light cloudy", "thunder", "hail", "drizzle", "smog". We associate weather observations to driving images by assigning the information from the nearest observatory according to the position information in probe data recorded by drive recorders. To unify the labels across different datasets, we remove "precipitation", "thunder", "hail", "drizzle", "smog", which have extremely low quantities and perform a mapping from the rest labels to BDD100K labels. Figure 3 summarizes the procedure.

Since the number of images is too large, we extract two sets from original driving videos according to the distance between the vehicle and the nearest observatory, which are "Kyushu 1 km" and "Kyushu 5 km" set. "x km" indicates that the distance is less or equal x km. The concrete number of images of each category can be viewed in Table 2.

Road Condition Labeling. To provide road condition labels, we label the test set of "Kyushu 1 km" manually for testing. During the labeling process, we prioritize the "road condition" information. Because we need to unify all the labels, and "partly cloudy", "overcast" as well as "foggy" don't have much connection with road conditions, we label "rainy" if the road is wet and "snowy" if the road has

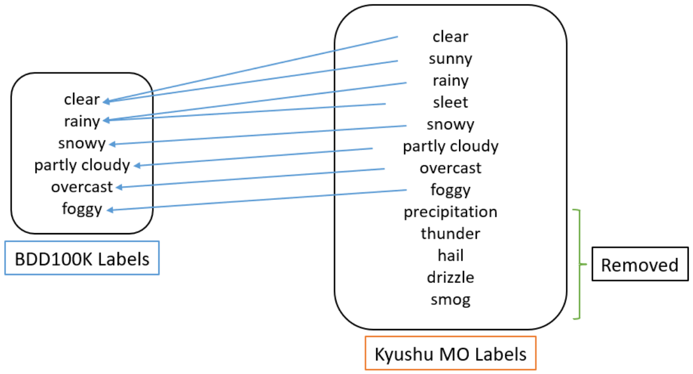


Fig. 3. The label mapping between the two datasets. "Clear" and "sunny" are merged to "clear". "Rainy" and "sleet" are merged to "rainy". "Precipitation", "thunder", "hail", "drizzle", "smog" are removed due to low quanlities.

snow accumulated. If the road condition doesn't belong to any of the 2 cases, we label the image by determining weather and choose a label from "clear", "partly cloudy", "overcast" and "foggy".

3.3 Deep Image Classification

Deep residual learning [3] have reached great success on various kinds of image recognition problems. With our prepared data, we train 3 deep models with ResNet50 with BDD100K training data, Kyushu 1 km training data and Kyushu 5 km training data and we evaluate the models with test/manual data.

Table 2. The quantities of each categories of BDD100K, Kyushu 1 km and Kyushu 5 km. Test data is selected from 10% of each categories of the original data. The rest 90% is used as training data. "Manual" means the manually labeled road conditions.

	BDD100K		Kyushu 1 km			Kyushu 5 km	
	Train	Test	Train	Test	Manual	Train	Test
Clear	12454	1764	1744	195	321	19522	2170
Rainy	2522	396	391	44	46	9655	1074
Snowy	2862	422	431	48	25	1865	208
Partly cloudy	4262	638	603	68	25	4325	481
Overcast	7551	1039	2665	297	235	20197	2245
Foggy	48	5	0	0	0	62	7
Total	29699	4264	5834	652	652	55626	6185

4 Experiments

4.1 Training Details

We train our networks with a single Nvidia GTX 2080Ti graphic card. The learning rate is 0.0001. We train each model 20 epochs with a batch size of 32. The loss function we use is the classical cross entropy loss [15] and the optimizer is set to be adam [7].

4.2 Test Accuracy

Table 3. The test results of the 3 models on 4 test datasets. Each row represents a test set and each column represents a model trained by the corresponding training set. "Kyushu 1 km manual" is the manually labeled road condition test set.

Training/Test set	BDD100K	Kyushu 1 km	Kyushu 5 km
BDD100K	**70.99%**	44.17%	44.85%
Kyushu 1 km	41.12%	**99.11%**	**96.58%**
Kyushu 1 km manual	39.34%	54.12%	53.22%
Kyushu 5 km	38.53%	49.94%	**95.33%**

Table 3 shows the evaluation results on each test dataset. From the result, we can observe the following points significantly.

1. Testing on corresponding datasets achieves relatively high performance. Especially for Kyushu data, weather estimation has good accuracy.
2. Testing on BDD100K with the model trained by BDD100K cannot achieve as much performance as testings on Kyushu data with models trained by corresponding Kyushu data.
3. All models trained weather information fail to perform well with manually labeled road condition test data.

4.3 Analysis

High Performance on Weather Estimation. From the above results, we can see a surprisingly high performance on weather estimation with models trained by meteorological observatory data. Usually, it is even hard for human to recognize the weather in a meteorological level from a single image taken by a drive recorder. This means that the deep network may have the ability to track small unaware features which can indicate meteorological information. Moreover, this high performance may also be related to the selection of training and test sets.

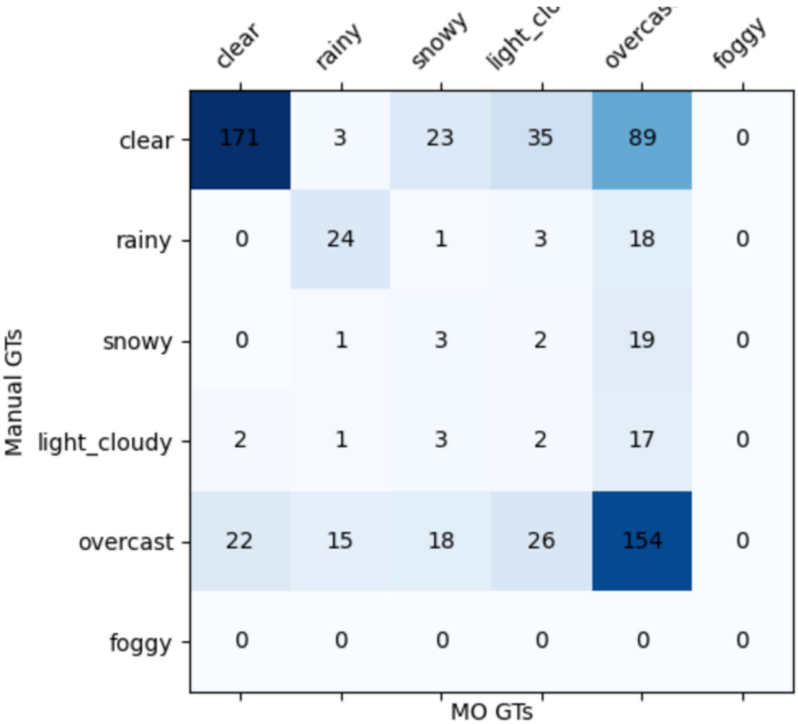
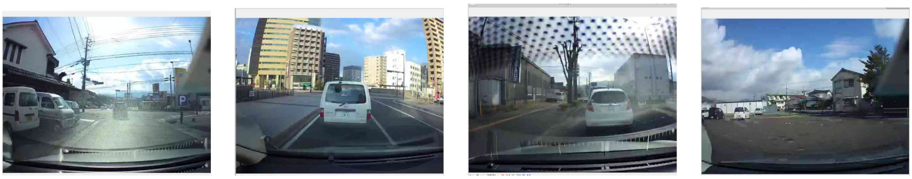


Fig. 4. A confusion matrix liked matrix that tends to show the difference between the meteorological test set and the manually labeled road condition test set of the Kyushu 1 km data. We manually labeled all images in the test set of Kyushu 1 km data with the same categories but a different idea. We first consider whether the road condition is "wet" or "snow", corresponding to "rainy" and "snowy", respectively. If the road condition is dry, we then consider the whole image and select a label from "clear", "light cloudy", "overcast" and "foggy" which can best describe the whole image.

Since we randomly select 10% of each categories, similar frames of a single sequence may be divided into both sets. Therefore, the test set of Kyushu data may not be distinguished from the training set clearly. However, even though the trained models may have bad extendable performance for other sequences, for "Kyushu 1 km manual", which has same data but different road condition labels, they cannot show a good performance, meaning that a model that can classify meteorological weather well cannot perform a good classification on road conditions.

Low Performance on Manually Labeled Set. As mentioned above, all models have bad performance on the manually labeled road condition dataset. We also explore the difference between this set and the original meteorological test set. Figure 4 displays a matrix that indicate the differences between the two sets. From the matrix, we can see that there are three kinds of main differences.

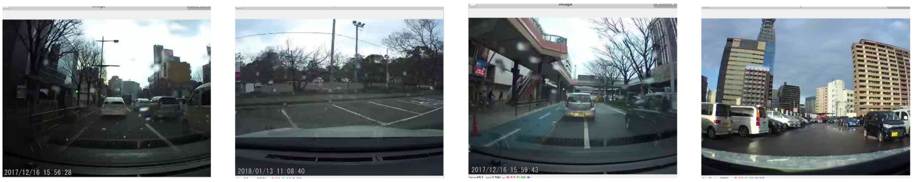
(a) Manual: clear. MO: rainy.



(b) Manual: clear. MO: snowy.

(c) Manual: overcast. MO: rainy.

(d) Manual: overcast. MO: snowy.



(e) Manual: rainy. MO: overcast.

(f) Manual: snowy. MO: overcast.

Fig. 5. Examples of images that produce difference between hand-labeled road conditions and meteorological weather attributes.

- Some non-clear images by MOs are labeled as clear.
- Some non-overcast images by MOs are labeled as overcast.
- Some overcast images by MOs are labeled by non-overcast.

We localize those images and show them in Fig. 5. Although because of the low resolution, a few mistakes can be seen for manual labeled images, (For example, the image in Fig. 5-a-2, we can see the reflection of the road, which indicates that the road is wet.) we can see that most images indicate that the actual road condition is different from the information from the nearest meteorological observatory, and the observatory makes the mistake. Typically as show in 5-e-4, we can see sunlight clearly, but the road is wet. In this situation, the most important factor that influence the driving behavior is the wet road condition, and the weather information here may lead to some certain misunderstandings.

5 Conclusions

In this work, we would like to raise the concern that the discrimination between road conditions and meteorological weather should be necessarily considered during the analysis of driving video data. We explore the public BDD100K data, and find out that the weather attributes in BDD100K are confused with road conditions. To provide pure weather information, we collect driving videos with probe data as well as weather information from meteorological observatories in Kyushu region. We train three deep neural networks using ResNet50 and test them on four test sets. As the result, meteorological weather estimation achieves a high performance, but fails to estimate road conditions. In addition, we localize concrete images find a significant discrimination between road conditions and weather.

5.1 Limitation and Future Work

Because of the training/test set selection strategy mentioned above, the models trained by Kyushu data in this work may be overfitting. Although a good accuracy is demonstrated, they may have bad extendable ability. Moreover, we haven't given a concrete definition of road conditions and only consider three aspects, which are dry, wet and snow.

As for the future work, we are going to first create a general dataset based on our Kyushu driving data. In the dataset, we are going to provide both the meteorological weather attributes and manually labeled road condition attributes. With this dataset, more supplement experiments of this work can be made and more precise driving data analysis can be done in the future. In addition, we will improve our weather estimation framework. Instead of trivial ResNet50, we plan to propose a new novel deep framework focusing on estimating various information such as weather, road conditions, wind from driving videos.

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