Proceedings of ACML-TAB2019

Vehicle anormality evaluation using probe trajectory data

Shintaro Takayama SHINTARO.TAKAYAMA.R5@DC.TOHOKU.AC.JP
Masao Kuwahara KUWAHARA@PLAN.CIVIL.TOHOKU.AC.JP
Yosuke Kawasaki KAWASAKI-Y@PLAN.CIVIL.TOHOKU.AC.JP
Shogo Umeda UMEDA@PLAN.CIVIL.TOHOKU.AC.JP
Koichi Hashimoto KOICHI@M.TOHOKU.AC.JP
Tohoku University

Abstract

Traffic disorders such as traffic jams occur in disasters and events, and lead to delay in evacuation, secondary disasters such as accidents, and traffic jams in various places. Therefore, it is important to grasp the traffic situation as soon as possible, specify the factors, and take countermeasures. In this paper, we propose a method to detect traffic faults using probe data of a region without limiting OD pairs and a method to classify abnormal behaviors due to traffic faults.

Keywords: Probe trajectory data, Traffic failure detection, Event

1. Introduction

In Japan, travel time loss due to traffic congestion is a serious problem. Therefore, it is necessary to grasp the traffic situation immediately, specify the cause, and take the countermeasure. As a resource for grasping traffic conditions, there is probe data which can acquire a wide range of vehicle trajectories in real time. In this paper, we propose a method to classify abnormal behaviors caused by traffic disturbances using probe trajectory data. As the result, it becomes possible to detect the abnormal vehicle in wide range and real time, and it can be expected to be useful for the cause investigation of the traffic disturbance.

2. Abnormal vehicle detection using TSD and DTW

To detect abnormal vehicles such as traffic jams and detours, two trajectories were compared by two similarity indices. One is Time Space Distance (TSD) proposed by Yoshida et al. (2018). This is useful for evaluating the difference in travel time between congestion and detour. The other is Dynamic Time Warping (DTW) proposed by Berndt and Clifford (1994). This is effective for evaluating the difference of the trajectory shape caused by the behavior such as detour. Using these two indices, traffic disturbance was detected and vehicle behavior was classified.

TSD evaluates the similarity between two trajectories by adding the difference of positions at each time point. Since TSD simultaneously sums the distances between points, it is considered to be effective for evaluating the similarity of trajectories due to the difference of travel time such as traffic jam and detour.

DTW is an index to evaluate the similarity by performing alignment and difference calculation of two shapes simultaneously. The DTW compares the difference between the positions of the two time series data at each time point, finds the minimum relationship (= Warping Path), calculates the sum of the Warping Path, and evaluates the similarity.

DTW is effective for evaluating the similarity of trajectory shapes, because the sum of warping paths becomes the similarity without considering time series information.

A method for classifying abnormal vehicle behavior using two similarity indices introduced in the previous section will be described. The abnormality of the vehicle is calculated using each similarity index, and the abnormal vehicle is classified using the correlation between each index. Here, the abnormality means to quantitatively evaluate how far the locus of the evaluation object deviates from the locus set.

By using the TSD that evaluates both the trajectory shape and travel time and the DTW that evaluates only the shape, vehicle behavior can be classified as follows.

Based on the characteristics of each index, the trajectories that affect both the shape and the travel time are classified as category 1, the trajectories that have a large deviation in the position of OD pairs and a large similarity in shape but a low similarity with the passage of travel time are classified as category 2, the trajectories that do not affect the shape but affect the travel time are classified as category 3, and the frequency trajectories that take the shortest paths that are not affected by the shape and the travel time are classified as category 4.

3. Conclusion

In this study, we propose a method to detect traffic obstacles using probe trajectory data. When the proposed method was verified using actual data, traffic obstacles were detected, vehicle behavior was classified, and abnormal vehicles such as detours and traffic jams were detected from a set of trajectories. In the future, we will compare the ratio and characteristics of abnormal vehicles in the event data set and the normal data set when there are traffic regulations that may affect traffic. The abnormal vehicle rate (a detour or a track that causes traffic jams) is expected to increase by traffic regulation, and the effect of traffic regulation on traffic is quantitatively evaluated by calculating the abnormal vehicle increase rate in normal time and event.

Acknowledgments

This research was supported by JSPS KAKENHI Grant Number JP16H06536. This research was supported by JSPS Grant-in-Aid for Scientific Research 26220906 and a research project commissioned by the National Institute of Information and Communications Technology (NICT), "Research and development of smart mobility infrastructure through data collaboration in different fields". The probe data (ETC2.0) used in this research was provided by the Tohoku Regional Development Bureau, Ministry of Land, Infrastructure, Transport and Tourism. I express my gratitude here.

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