Automatic Classification of Traffic Accident Using Velocity and Acceleration Data of Drive Recorder

Moe Miyata(✉), Kojiro Matsuo, and Ren Omura

1-1, Hibari-ga-oka, Tnepaku-cho, Toyohashi, Aichi 441-8580, Japan
miyata@usl.tut.ac.jp, k-matsuo@ace.tut.ac.jp,
ren@tut.jp

Abstract. In recent years, a drive recorder becomes common and is installed in a car to record sensor data, such as images, acceleration, and speed, about driving. The recorded data is useful to confirm and analyze a dangerous driving scene of a traffic accident and an incident. However, analyzing such data takes long time because it is done by a person who checks data one by one. Therefore, a method of automatic classification of drive recorder data is explored in this study. First, we labeled three types of incidents on the recorded data. Then, after extracting features from the acceleration and velocity, machine learning techniques are applied for the classification. Our preliminary evaluation showed that the classification result achieved about 0.55 of f-measure value.

Keywords: Acceleration · Classification · Machine learning · Drive recorder

1 Introduction

In recent year, a drive recorder [1] becomes common, and are installed in many cars. It records driving conditions, such as acceleration, braking, and turn signal, and video data, before and after getting an impact by some reasons. The recorded data are useful to confirm a dangerous driving scene of a traffic accident and an incident where a car accident almost happens. However, in many cases, analyzing data takes long time because it requires a person to check it one by one.

Some existing studies addressed a method to analyze and classify recorded data automatically. Kubo and Midori proposed a method to automatically classify the data using acceleration waveform [2]. In their study, videos of driving recorder obtained from taxis are confirmed by authors and labeled by ten types of incidents. Then, classification rules that classify the data into 7 types was manually constructed based on observed characteristics of acceleration waveform and was implemented as a software. As a result, Kappa coefficient between automatic classification result and visual confirmation result showed 0.73.

In recent years, sophisticated machine learning technique is available and is expected to show better classification performance. Takenaka *et al.* proposed a method to pick up a certain event in a video recorded by a drive recorder using sensor data [3]. This study classified some situations of driving, such as acceleration, deceleration, and

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curve, with sensor data as semantic information of driving. By summarizing these semantic information, the data was labeled with more abstracted driving situation, such as normal progress, downhill, and change lanes. For detecting an event, several frames of the video before and after the point where label changes were automatically picked up and displayed in an analyzing software. However, the event type of picked up data had to be confirmed manually. Also, since the method is based on video analysis, it requires high calculation load when analyzing data of whole day.

NTT Communications proposed a method to automatically identify an incident of "crossing collision" using deep learning algorithm with the combination of image and acceleration data recorded by a drive recorder [4]. They used 9000 drive recorder's data of collaborative research company, and the result showed 85% of precision [5]. In addition, another study of them also confirmed the same method can automatically identify "stop sign violation" with 89% of true positive rate [6]. These studies can be expected to be useful for an analysis to prevent accidents. However, these studies have identified only one type of incident and do not identify multiple accident simultaneously.

Therefore, we study a method to automatically classify multiple types of driving incident using machine learning technique with simple sensor data of acceleration and speed recorded as a small amount of data around an event. In our study, more than 12376 drive recorder data are checked and labeled into three types of incidents, and we obtained 396 data in each incident type (1188 data in total). Multiple ranges of sensor data for extracting 41 dimensional feature values were explored to obtain better performance of classification. Moreover, several types of classification algorithm of supervised learning were evaluated and compared.

In the next section and Sect. 3, the recorded data and labeled data used in this study are explained. Sections 4 and 5 describes extracted feature values and machine learning algorithm. Section 6 shows the results of evaluation. Section 7 conclude this study.

2 Recorded Data

The sensor data used in this study was recorded by driving recorders installed in 224 taxis of a taxi company in Toyohashi city, Aichi prefecture, Japan. All recorded data was recorded from August 26, 2006 to December 14, 2011. The driving recorder records data 12 s before and 8 s after an event happens on the two-dimensional acceleration sensor (20 s in total before and after the event). The event is defined as a timing where the acceleration sensor observes more than 0.4 G on either the x or the y axis. The driving recorder records video, two-dimensional acceleration (vertical and horizontal), date and time, and the number of rotation of the tire of the car as its speed, on each frame at about 7 fps. As a result, one recorded data consists of 20 s of video and 135 frames of sensor data. In addition, the sizes of the tire of the cars are stored separately in another table.

Each recorded data is labeled into three types, "collision", "in passing another", and "others". "Collision" is a case that a rear vehicle collided with a front vehicle during vehicles traveling in the same direction [7]. "In passing another" is a case that vehicles going opposite direction collides. "Others" includes the cases where no accident happens but an event occurs, such as car bounds and sharp curves, as well as an accident other than “collision” and “in passing another”.

We obtained 12376 recorded data in total. First, all the recorded data were roughly labeled as 462 data of “Collision”, 1577 data of “in passing another”, and 10337 data of “Other”. Then, the videos are confirmed, and unobvious cases are eliminated.

3 Learning Data

We visually checked the video, recorded sensor data (frame number, number of rotations of the tire, horizontal and vertical acceleration value), and car information.

First, we confirmed the record data labeled “collision” of all recorded data. Since “collision” has the smallest number of recorded data in three types, the number of it was considered as the base line for the total number of learning data on each label. When the video was ambiguous with the definition of the label, the data was excluded from the learning data, which is named “pending data”. When the recorded data corresponded to the conditions in Table 1, the data was also excluded from learning data, which is named “exclusion data”. As the result, 396 learning data labeled “Collision” were obtained. By spending similar process, 396 cases of learning data labeled “in passing another” and learning data labeled “others” are obtained.

Table 1. Definition of exclusion data

Condition name	Explanation
Traffic accident	There is a contact accident of two or more cars
Incomplete frame	Number of frames is less than 135
No car information	There is no car number, or the size of the tire of the car is unknown
Incomplete hertz	Although the car equipped with the event data recorder is in progress, the rotation speed of the recorded tire is 0.0 [km/h]

Table 2 shows the confirmation results of recorded data. “Total” indicates the initial number of number of each data. “Pending” indicates the number of recorded data classified as pending data, “exclusion” indicates the number of recorded data classified as exclusion data. Learning data indicates the number of recorded data classified as learning data. Finally, 396 labeled data of each incident type are exploited for machine learning.

Table 2. Result of recorded data

Label name	Total	Pending	Exclusion	Learning data
Collision	462	50	16	396
In passing another	623	208	19	396
Others	530	109	25	396

4 Extracting Feature Value

Feature values used in machine learning were extracted from learning data selected in Sect. 3. First, velocity was calculated from the number of rotations of the tire and the size of the tire for each car using the Eq. (1) [8]. In this equation, V is the velocity of the car between two frames, H is the number of tire rotations per frame, n_1 is a constant determined by the size of the tire of the car, and N_2 is a constant of 637 [rpm].

$$V = \{H * 60\,[s] * 60\,[Km/s]\}/\{n_1 * N_2\} \tag{1}$$

Next, each feature values were calculated from the speed, vertical acceleration, horizontal acceleration, and combined acceleration in certain ranges of sensor data. For investigating the useful range of sensor data, the ranges for extracting feature values ware varied as shown in Table 3. 10 kinds of feature values are calculated; maximum value, minimum value, average value, standard deviation, zero cross rate, peak frequency, frequency entropy, kurtosis, skewness, spire degree [2]. Discrete Fourier transform (DFT) was used to calculate the peak frequency and frequency entropy. As the result, 40 features are exploited for machine learning.

Table 3. Feature values extraction range of acquisition

Range of acquisition [s]	Explanation	Number of total frame
0–20	From start recording to end	135
0–12	From start recording to the sensor reacts	81
12–20	The sensor reacts to end of recording	54
11–13	Before and after sensor reaction 1 s	14
9–15	Before and after sensor reaction 3 s	40
7–17	Before and after sensor reaction 5 s	68

5 Machine Learning

For the evaluation, a free machine learning software, "Weka" [9], was used. We converted feature values to ARFF files, which is data format for Weka. As the classification algorithm of machine learning, nearest neighbor algorithm (kNN, k = 1), random forest (RF), and support vector machine (SVM) were tested. The reason for choosing RF and SVM is that they are not affected by the curse of dimensionality very well. The evaluation is done by 10-fold cross validations using 396 training data (instances) for each class, 1188 instances in total. As the criteria of the classification performance, averaged accuracy, averaged F-measure values, and Kappa coefficient ware reviewed.

6 Result

The results are shown by Fig. 1 (a) to (c). From these results, the best performance for each evaluation is: (a) 0.70 of accuracy with the acquisition range of 7–17 using RF, (b) 0.55 of F-measure in the acquisition range of 7–17 using RF, (c) 0.33 of the Kappa coefficient in the acquisition range of 7–17 using RF. All results showed that the best performance gives with the acquisition range of 7–17 using RF.

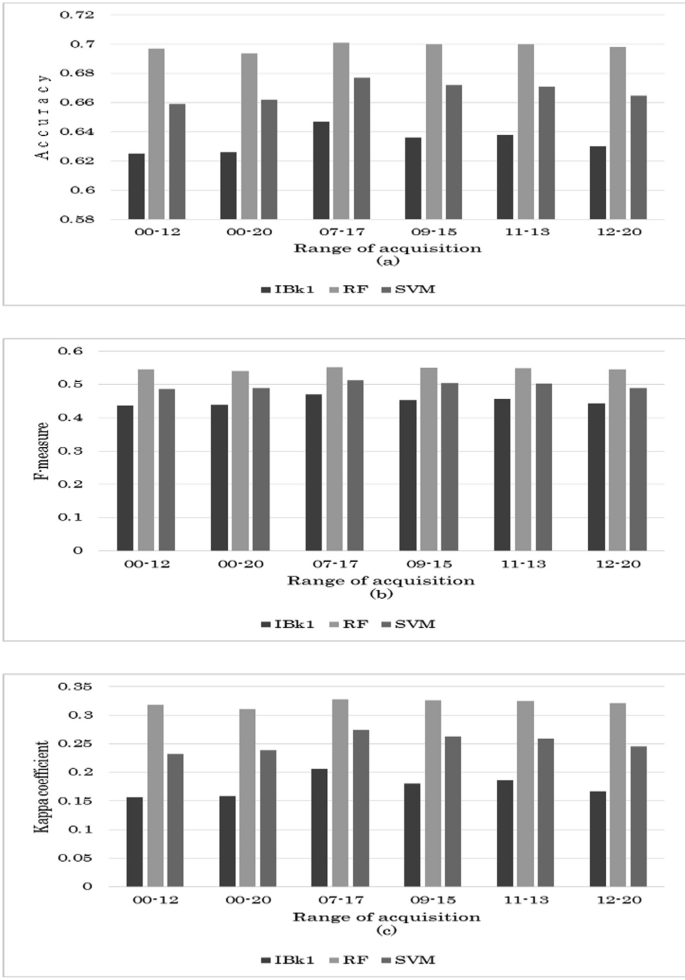

Fig. 1. Result with 396 learning data (10-folds cross validation). The horizontal axis represents the acquisition range, and the vertical axis represents the value of each criteria; (a) averaged accuracy, (b) averaged F-measure, (c) Kappa coefficient.

7 Conclusion

We studied a method to automatically classify driving incidents using acceleration and speed data recorded by a driving recorder with machine learning techniques. Using the 41 feature values, we compared the several ranges of sensor data used for feature extraction, 0–20, 0–12, 12–20, 11–13, 9–15, and 7–17, and three types of classification algorithms, nearest neighbour algorithm, SVM and random forest. The evaluation showed that the classification result achieved the best performance, 0.70 of accuracy, 0.55 of F-measure, 0.33 of Kappa coefficient, with the range of 7–17 using RF.

References

1. Safety measures for business vehicles: vehicle comprehensive safety information (in Japanese). http://www.mlit.go.jp/jidosha/anzen/03driverec/dorareco.html
2. Kubo, N., Midori, M.: Efficient automatic classification method of drive recorder. Trans. Jpn. Soc. Mech. Eng. Ser. (C) **77**(778), 338–353 (2011). (in Japanese)
3. Takenaka, K., Bando, T., Nagasaka, S., Taniguchi, T.: Drive video summarization based on double articulation structure of driving behavior. In: MM 2012 Proceedings of the 20th ACM International Conference on Multimedia, pp. 1169–1172 (2012)
4. News September 26, 2016: Succeeded in automatic detection of dangerous driving using artificial intelligence (AI) – NTT Com Corporate Information, NTT Communications Company Information (in Japanese). http://www.ntt.com/about-us/press-releases/news/article/2016/20160926_2.html
5. NTT Com: Successful automatic detection of dangerous driving using AI (in Japanese). http://www.atmarkit.co.jp/ait/articles/1609/27/news117.html
6. NTT Com and NCS: 96% probability to detect a temporary stop violation from video of drive recorder (in Japanese). https://it.impressbm.co.jp/articles/-/15087
7. Traffic Accident Statistics Glossary (in Japanese). https://www.itarda.or.jp/service/term.php
8. Japanee Industrial Standards JIS D 5601 – 1992 Automobiles speedometer (in Japanese)
9. Weka 3 - Data Mining with Open Source Machine Learning Software in Java. https://www.cs.waikato.ac.nz/ml/weka/