Deep Learning for Driver Identification with DTW Common Track Verification

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Abstract

Each person has his/her own driving style, which can be used to identify the driver. Mining driving characteristics or habits from numerous travel data to identify drivers is the Driver Identification topic concerned in this paper. Real data sets are collected, including GPS, Acceleration and Angular Velocity. Some Deep Learning algorithms, such as AlexNet and Recurrent Neural Network, are novelly applied to solve the problem. Moreover, their performance are compared with Multilayer Perceptron and Random Forest in Machine Learning. In addition, drawing on the idea of speech recognition, Dynamic Time Warping is applied to find common track sections as verification set for Deep Learning identifications, which is a brand new crossover application. The overall designed identification process is tested by experiments, in which 5,500,000 driving records for each of 25 drivers are collected, and accuracy, precision, recall, verification rate and speed are consided as perfomances. The results show that Deep Learning are feasible for the problem and the two algorithms have different advantages. Especially, the testing accuracy of AlexNet is 46.15%, and the DTW verification accuracy can reach 67.77% . The methods proposed in the paper can be widely applied to similar problems in traffic, such as fleet drivers identification.

Key words: Driver Identification, Deep Learning, Machine Learning, Dynamic Time Warping.

Introduction

It is possible to identify drivers according to different driving behaviors revealed by time series data (Zhang Xingyao 2014) [1]. A driver's behaviors are affected by traffic conditions, accidents, and even weather. However, the effects of these short-term, accidental factors can be weakened in background of considerable data.This is one of the reasons that the amount of experimental data should be large.

Digging out unique driving behaviors based on labeled driving sensor data, which consist of latitude, longitude, acceleration and angular velocity, etc., and using some classifiers to identify drivers, is the Driver Identification mentioned. To make sure the identification is exactly for drivers, all external conditions should be as equal as possible. So the same data-collection principles for vehicles were taken. Furthermore, if a classifier can recognize the true diver or drivers of the same car and the same route, it will be much more convincing for the identification. And that is why the Dynamic Time Warping (DTW) is used to search the Common track sections as verification set for methods validation outside the test set.. *Figure 5* shows the overall process of the driver identification method.

Classifiers in Machine Learning (ML) and Deep Learning(DL) are widely used on driver identification such as [2-5], which related to human face, iris, voice, and other biometric features. In this paper, AlexNet and RNN with LSTM in Deep Learning are chosen and differently used on sensor data analysis. Driver Identification by DL and ML has applicability in detecting claims fraud, accident accountability, theft tracking and designing IDSS[6]. The method can even be used in fleet drivers identification and estimating the number of drivers actually sharing the car. The most important thing is that it is much easier than image processing in [2-5].

The rest of this paper is structured as follows. In next Section, some related works are reviewed. Section 3 introduces the data collected and its preprocessing. Section 4 presents the algorithms we used.

The experiments, its results and analysis are shown in Section 5, before the final summaries and outlook are drawn in Section 6.

Literature Review

The research about driver identification can be summarized as three categories.

a. Driver identification by the vehicle control behavior of the driver.

Miyajima C and Nishiwaki Y.(2007) pointed out that different drivers have their own habits in starting, turning, speeding, following and so on. The distribution of the pedal operation signal or spectrum feature extracted by spectrum analysis can be used in recognition of the driver.

Filev D, Lu J. et al. (2009) studied how to express driving behavior or structure of driver's control to distinguish the driver from active or cautious driving behavior.

Based on the driving simulation data obtained from the comprehensive experimental platform, Zhang Xingyao (2014) analyzed the characteristics of the driver's step-by-step clutch, braking, acceleration and steering. And by combining the relationship in the vehicle status, such as characteristics of vehicle operation stability and speed change, with the driver's operation, it is able to identify the driver who is drink driving[1].

These are some researches on drivers' different control behaviors in special condition such as drunk driving or fatigue driving. But most of them are not for individual identification.

b. Driver identification by the driver's biometric characteristics.

Some biometric characteristics, like face, eyes, finger veins, the nerve and muscle properties of arms, key points of skeleton, have been studied to identify drivers based on image and signal processing.

For example, JD Wu and SH Ye (2009) designed a system that uses finger vein technology along with the artificial neural network for driver identification[3]. Chen Y. S. et al. (2011) has developed a technique for matching driver face images by serial image processing [5].Yuan M. et al. (2012) proposed a method based on the eye and facial expression features to determine whether there is fatigue driving.

These methods possess high recognition accuracy, but require complicated equipment and processes, and are greatly influenced by the environment.

c. Driver identification by analyzing the sensor data of the car.

This is the category this paper also belong to. There are many studies on driving behavior analysis based on time series, such as [8-11]. Those need the support of good hardware and software. In recent years, there have been some attempt to apply ML and DL. Liu H et al. (2015) proposed a DSAE method for extracting key features from redundant driving behavior data[12]. Dong Ward et al. (2016) used CNN and RNN to describe driving behavior on GPS data[6]. And Zheng-ping Li et al.(2017) has done a similar research to our work by using ML in driving acceleration data[13], but it has no verification.

Trajectory similarity measure and common track finding. Additionally, along with the same principles of data collection, recognizing driver or drivers on common route sections is necessary and useful to verify the effectiveness of algorithms. And a lot of researches have been done for trajectory similarity measure. Typical examples are Euclidean, DTW, LCSS and ERP [14-16]. Considering samples are affected by speed and pause duration, the DTW is chosen.

Experiment Data

Data Collection

We collected data include GPS data Six-Axis data and for 25 drivers. Considering traffic, we collected data from 9:00am to 11:00am or from 15:00 pm to 17:00pm for drivers in over one week. It means that more than 5,500,000 records in total for each driver are collected.

The left-right, front-rear and up-down direction of vehicles in geodetic coordinate system is defined as *x*, *y* and *z* direction, respectively. GPS data includes longitude and latitude, of which sampling interval is 1s. The six-axis data are arranged in the acceleration of *x*, *y* and *z* directions, followed by the angular velocity of *x*, *y* and *z* directions, with 0.01s sampling interval.

Data Preprocessing

Calibration. Sensors' installation follow the same principle. However, there may be some slight differences mainly on the deviation between the actual axial direction of the sensor and the default geodetic coordinate system. So data calibration is necessary. Using coordinate transformation to calibrate the acceleration data a_x, a_y, a_z [13], a coordinate transformation matrix example for one of the drivers is

$$R=\begin{bmatrix} 0.79933 & 0.99563 & -0.04817 \\ -0.99469 & 0.08281 & 0.06114 \\ 0.06486 & -0.04303 & 0.99697 \end{bmatrix}$$

Finding common section. Step1, Narrowing the target to a busy area. After dropping outliers, the overall trajectory are plotted in the *Figure 1(a)*. The darker the color, the busier these points may be. In *Figure 1(b)*, one color presents one driver, and the busier areas can make it easier to find drivers with common driving sections. In fact, the road network plotted fits well with the real map (*Figure 1(c)*).

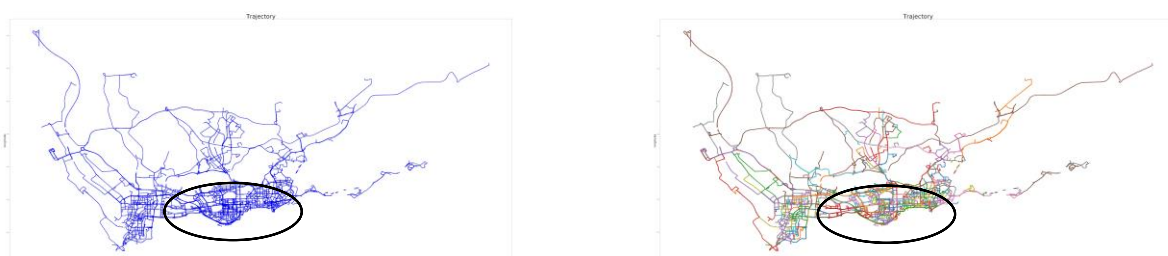


Figure 1. (a) The overall trajectory of 25 vehicles. (b)The routes of each driver

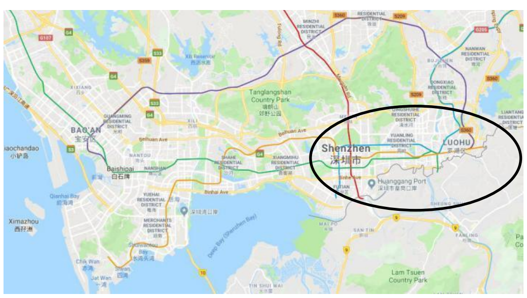


Figure 1. (c) The actual area map

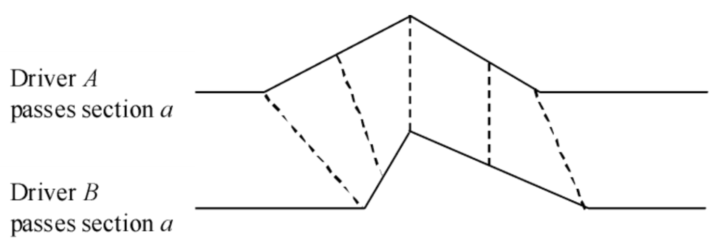


Figure 2. Using DTW to match the same section with different speeds

Step 2, Detecting the same road segments by Dynamic Time Warping (DTW). The driving trajectory sampling is affected by the speed and pause duration, so the same road section may have different length of samples. DTW is well known in speech recognition to cope with different speaking speeds[14]. It is used now to measure similarity between two sections of trajectory with different speed (*Figure 2*) which will be separated as verification set.

The formulas *(1)* are used to find similar track record segments with small DTW distances.Where *m* and *n* are the lengths of the segments *a* and *b*. As an example, three similar route segments from the data set extracted by DTW are shown in *Figure 3*.

$$\begin{cases} DTW(a,b)=\min\{C(a,b)\} \\ C(a,b)=\sqrt{r(i,j)},\ i=[1,n],\ j=[1,m] \\ r(i,1)=\sum_{k=1}^{i} C(a_k,b_1),\ r(1,j)=\sum_{k=1}^{j} C(a_1,b_i) \\ r(i,j)=C(i,j)+\min\{r(i-1,j),r(i,j-1),r(i-1,j-1)\} \end{cases} \tag{1}$$

c. Features extraction and selection. Six variables, namely 6 axes, along with the backward differences of them constitute the original variables space. Because vehicles' status will not change suddenly in interval 1/100s. So, we delete outliers and fill missing data with the previous record of them. Then sliding window was use to extract statistical characteristics (*Figure 4*). Taking window size *Ls=1000*, that is 10s equivalently. And let the stride *Lf* be *Ls/2* (ie. 500). Then 7 statistical characteristics, namely mean, minimum, maximum, 25% quantile, median, 75% quantiles and standard deviation, are chosen to generate the feature vectors. Therefore, 12*7=84 features and more than 10,000 feature samples for each driver are generated.

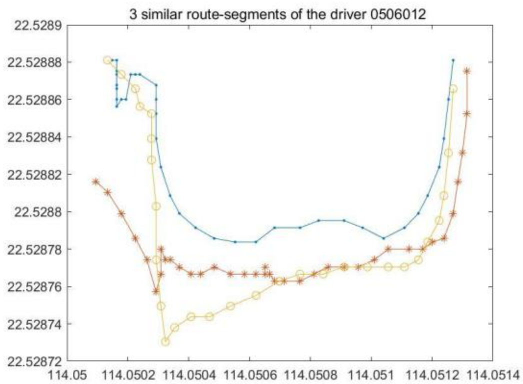


Figure 3. Several similar route segments

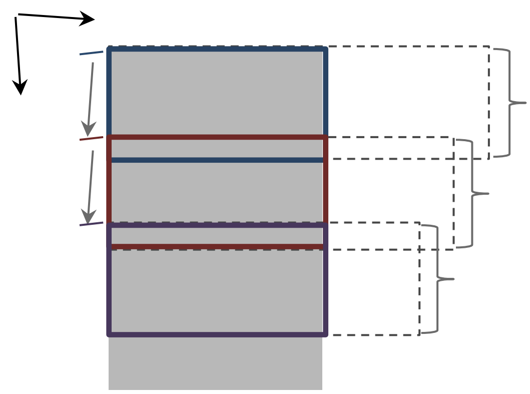


Figure 4. Sliding window processing in time series data.

Algorithms

To compare the performance of DL and other ML methods in driver recognition, typical methods such as AlexNet of CNN and RNN with LSTM are chosen from DL, and MLP and Random Forest are selected from ML methods.

Alexnet of CNN

It is meaningless to take convolution at feature dimension in this problem, so the 1-D convolution is used in CNN. The AlexNet-like sequential network is designed as *Table 1*.Where configure the model, the loss parameter is chosen as "*categorical_ crossentropy*", the optimizer is "*adam*", the performance metrics includes "*accuracy*", "*precision*" and "*recall*". Furthermore, the "*batch_size*" and the "*nb_epoch*" default to be 32 and 20.

RNN

The RNN sequential network designed composes of 6 LSTM layers and two all-connected layer (*Table 2*). The configuration parameters are same as CNN except the optimizer to be 'rmsprop'. In addition, the "*nb_epoch*" default to be 30. And the number of categories equal to the number of drivers (i.e. 25).

Multilayer Perceptron Algorithm (MLP)

"*relu*" and "*adam*" are also the activation function and the optimizer when building a MLP neural network. The network is with 100 hidden layers. Furthermore,the *L2* penalty parameter and the initial learning rate set as 0.0001 and 0.001 [15]. 5-fold cross-validation is also used.

In addition, when the input data of the MLP algorithm are randomly sampled, the results recorded as MLP with Random.

Random Forest (RF)

The number of trees in the forest is 25. And the input data of the algorithm are also randomly sampled.

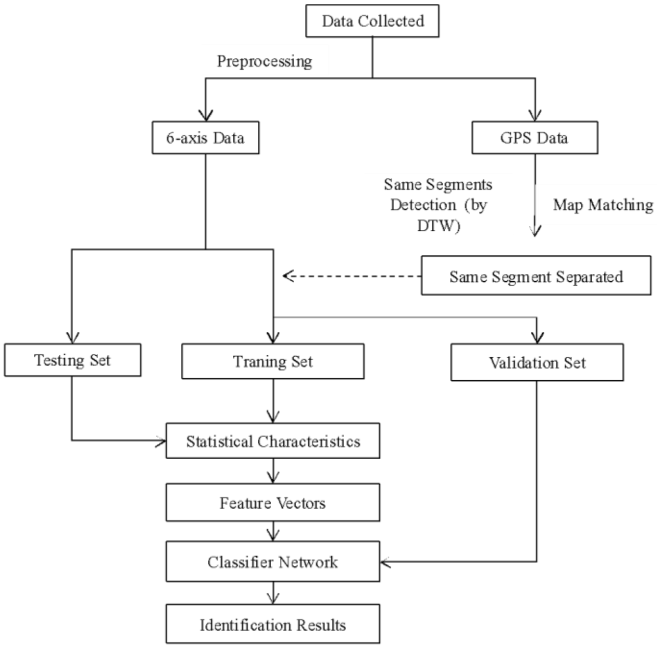
Table 1. The Structure of CNN with AlexNet framework

The structure of CNN (AlexNet-like)		
Layer(type)	Output Shape	Activation
conv1d_1 (Conv1D)	(None, 1, 64)	relu
MaxPooling1D	(None, 1, 64)	
conv1d_2 (Conv1D)	(None, 1, 96)	relu
MaxPooling1D	(None, 1, 96)	
conv1d_3 (Conv1D)	(None, 1, 256)	relu
conv1d_4 (Conv1D)	(None, 1, 256)	relu
conv1d_5 (Conv1D)	(None, 1, 96)	relu
MaxPooling1D	(None, 1, 96)	
flatten_1 (Flatten)	(None, 96)	
dense_1 (Dense)	(None, 800)	relu
dense_2 (Dense)	(None, 800)	relu
dense_3 (Dense)	(None, 25)	softmax

Table 2. The Structure of RNN with LSTM

The stucture of RNN (LSTM)	
Layer (type)	Output Shape
lstm_1 (LSTM)	(None, 1, 32)
lstm_2 (LSTM)	(None, 1, 64)
lstm_3 (LSTM)	(None, 1, 128)
lstm_4 (LSTM)	(None, 1, 32)
lstm_5 (LSTM)	(None, 1, 32)
lstm_6 (LSTM)	(None, 32)
dense_1 (Dense)	(None, 64)(softmax)
dense_2 (Dense)	(None, 25)(softmax)

	Precision %	Recall%	Testing Accuracy %	Verification Accuracy%	Speed(s)
AlexNet	91.33%	90.71%	46.15%	67.77%	318s
RNN(LSTM8)	81.28%	38.61%	13.33%	33.27%	44s



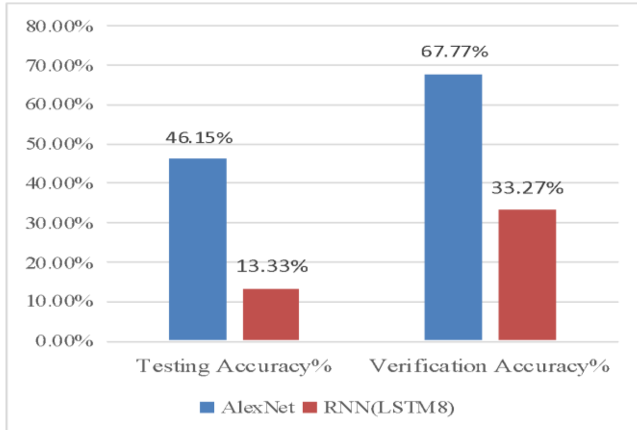


Figure 5.(left) The structure of experiments designed

Table 3.(right) The precision, recall , accuracy in testing and verification, and speed for chosen algorithms in DL .

Figure 6.(right) The Testing accuracy and verification accuracy for two chosen algorithms in DL

Experiments

We separated the same road segments with small DTW distance for the final validation, the remaining for learning and testing. *Figure 5* shows the structure of experiment for the driver identification method. Some parameters were set as Section 3 and 4 mentioned. we took Ls=1000 and Lf=500 for feature extraction and constructed about 10,000 feature samples for each driver from over 5,500,000 raw records for everyone. Specifically, we settled 125173 samples on training, 61653 samples on testing, and 21042 samples separated by DTW for validation.

Deep Learning Performances Analysis

The precision, recall, accuracy in testing and DTW verification, and spending time in each epoch of Alexnet and RNN are shown on *Table 3 and Figure 6*. From this we can get that:

a. All scores of Alexnet and RNN are higher than 4% (random guess), which shows the two are feasible in driver identification. The highest accuracy in testing set and verification set are both from Alexnet, 46.15% and 66.77% respectively.

b. Both accuracy in testing and verification of Alexnet are higher than RNN with LSTM, which means that Alexnet structure may be more useful than RNN in this problem, or RNN has space to be tuned.

c. While as for speed, the RNN takes the advantage for being faster than Alexnet in every epoch.

d. Accuracy in DTW common track verification set is better than in testing set, that may indicate that the two learning methods are easier to recognize the driver or drivers in many common tracks. And this also makes the identification more convincing.

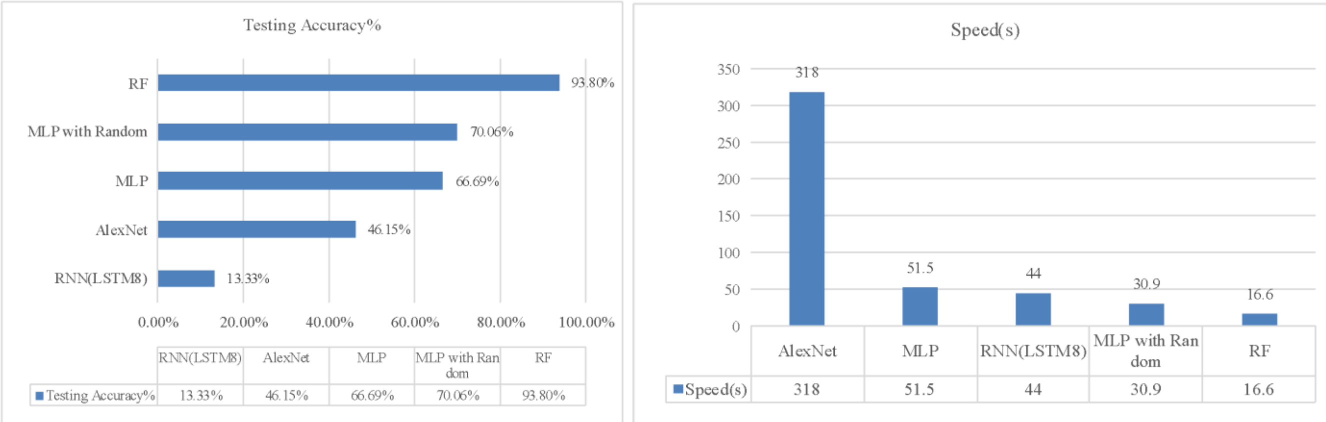


Figure 7. The testing accuracy and spending time for the algorithms.

Comparative Analysis

The testing accuracy and speed of the two DL clasifiers and three other ML classifiers are shown on *Figure 7*. From which we can get that:

The Deep Learning and the Machine Learning algorithms chosen are all feasible in driver identification based on travel data.

For the testing accuracy of classifiers, both two in deep learning cannot match the three other in machine leaning. The reason here is worth further exploration.

For the spending time of one epoch or loop, AlexNet takes the longest of 318s, RNN is faster than MLP in Machine learning.

Considering both accuracy and speed, deep learning may not be as good as Random Forest in machine learning.

Conclusion

We collect, clean, calibrate and extract feature from 5,500,000 driving records for each of 25 drivers, and we use DTW to help us separating the commom route sections for verification. Then AlexNet, LSTM in Deep Learning are chosen as identification classifiers and compared in the term of precision, recall, testing accuracy, verification accuracy and calculation speed. Moreover, the testing accuracy and speed of them are used to compare with MLP and Ramdom Forest in Machine Learning.

AlexNet and RNN with LSTM are both feasible and credible in identification. Especially, AlexNet performs better on testing and verification accuracy, with scores of 46.15% and 67.77% respectively. While RNN takes a faster speed advantage. Hower, considering both accuracy and speed, they need to be improved to catch the performances of the Random Forest algorithm in machine learning.

This work obtains several improvements than previous works. Firstly, It collects a larger number of data which can make the results more convincing and more practical. Secondly, it ensures that all unrelated factors to the driver being consistent. Especially, the common route sections are separated by DTW for verification. Thirdly, it could also work even if there are multiple drivers of one vehicle. So it could be applied in traffic big data analysis such as fleet drivers identification and estimation of the number of drivers actually sharing one vehicle.

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