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Efficient normalization for quantitative evaluation of the driving behavior using a gated auto-encoder*

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Abstract: Driving behavior normalization is important for a fair evaluation of the driving style. The longitudinal control of a vehicle is investigated in this study. The normalization task can be considered as mapping of the driving behavior in a different environment to the uniform condition. Unlike the model-based approach as in previous work, where a necessary driver model is employed to conduct the driving cycle test, the approach we propose directly normalizes the driving behavior using an auto-encoder (AE) when following a standard speed profile. To ensure a positive correlation between the vehicle speed and driving behavior, a gate constraint is imposed in between the encoder and decoder to form a gated AE (gAE). This approach is model-free and efficient. The proposed approach is tested for consistency with the model-based approach and for its applications to quantitative evaluation of the driving behavior and fuel consumption analysis. Simulations are conducted to verify the effectiveness of the proposed scheme.

Key words: Driving behavior; Normalization; Gated auto-encoder; Quantitative evaluation
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1 Introduction

Quantitative evaluation of the human driving behavior is an important research topic in both the automobile industry and intelligent transportation (Kaplan et al., 2015). The longitudinal control of a vehicle addressed in this work is an essential part of the driving behavior. According to the Traffic Administration Bureau of the Ministry of Public Security of China (TAB, 2010), about over 90% of traffic accidents are attributable to human drivers. Research in psychology and cognitive science (Al-Sultan et al., 2013) indicates that the driving behavior is a complex decision-making process with affecting factors such as the environment, vehicle, and driver. Note that even a moderate driver will make frequent operation of gas/brake pedals in heavy traffic or on hilly roads, acting like an aggressive driver. For correct evaluation, it is therefore essential to normalize the driving behavior in an identical condition by eliminating the influence of the environment.

Many studies have been conducted on driving behavior analysis over past decades. A comprehensive literature review addressed the evolution of driving behavior modeling (Ranney, 1994). The methods employed include the motivation theory, visual search, control theory, and information processing. The established models can accomplish tasks such as risk avoidance, road identification, gear prediction, braking, and steering control. Other related methods can be classified roughly into three groups: (1) signal processing based methods, using wavelet transforms, fast Fourier transforms, and principal component analysis (PCA) to analyze and identify the patterns that reflect the driving behaviors (Zhang YL et al., 2010; Hu et al., 2013; Shi et al., 2015a); (2) model-based methods, establishing a driver–vehicle–

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environment model based on vehicle dynamics and the control theory to study and classify the driving behavior (Plöchl and Edelmann, 2007; Imamura et al., 2008; Filev et al., 2009); (3) artificial intelligence based methods, using neural networks, including deep learning, to fulfill tasks such as driving style recognition, target speed following, and fuel consumption evaluation (Xu et al., 2015; Wang YH and Ho, 2018; Zhang Y et al., 2019). In addition, hybrid approaches have been used in driving behavior analysis. A hybrid diver model based on cognitive driving data and the simulation tool, smartAHS, was proposed to compare the simulated behaviors of semi-automated vehicles and human drivers (Song et al., 2000). Cao et al. (2017) exploited raw vehicle data and employed a hybrid scheme based on the random forest approach to detect and compare different features, classifiers, and filters in driving events. Chen et al. (2019) studied the risky driving behavior based on nonnegativity-constrained auto-encoders, and extracted the hidden features of driving behaviors automatically for the risk prediction (Chen et al., 2019). Wang WS (2020) developed a Bayesian nonparametric method by integrating a hierarchical Dirichlet process (HDP) with a hidden Markov model (HMM) to extract driving primitives from sequential maneuvering data. These and other unmentioned works have made significant contributions to the advancement of the driving behavior analysis. One issue rarely addressed is the normalization of the driving behavior. This is important for driving style evaluation, since vehicle data is usually collected under different conditions, providing an unequal basis for comparison.

A model-based normalization approach was proposed in our previous work (Shi et al., 2015b). The personalized driver model was first established using real-world vehicle test data (VTD) of a certain human driver, and then employed as the virtual driver to conduct the speed-following task as defined by the standard driving cycle test, e.g., FTP-72. In this way, the raw driving behavior is normalized by conducting a virtual driving cycle test. This approach is effective for normalizing the driving behavior, but it is somewhat complicated and time-consuming because of the need to establish the driver model and to conduct the virtual driving cycle test.

This work presents a novel driving behavior normalization strategy with a special focus on longitudinal control. The normalization of the driving behaviors can be considered as the mapping of the driving behaviors in different conditions to the same condition. We propose to accomplish this task using the auto-encoder (AE) when following a standard speed profile. The research route is illustrated in Fig. 1. To ensure a positive correlation between the vehicle speed and driving behavior, a gate constraint is imposed between the encoder and decoder to form a gated AE (gAE). The main contributions of this work are as follows: (1) Without the need to establish virtual driver models, the proposed gAE approach is model-free and more efficient in driving style analysis; (2) The normalization scheme could be validated on its consistency with the model-based approach and raw data; (3) The extended applications of the proposed method include not only driving behavior evaluation but also fuel consumption analysis.

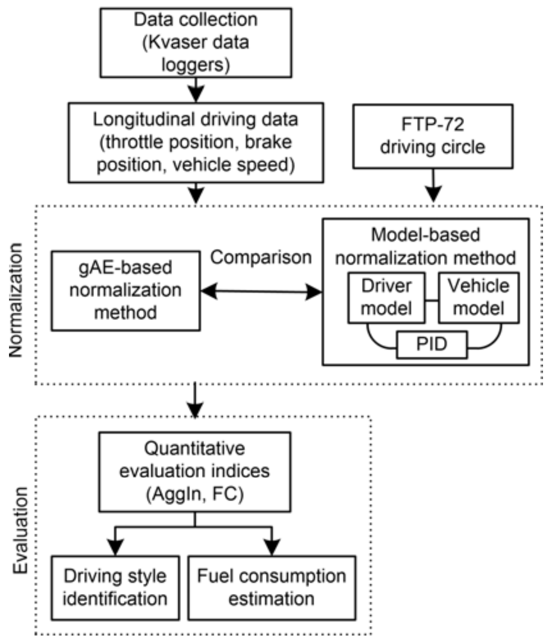

Fig. 1 Flowchart of the research route (gAE: gated auto-encoder; PID: proportional integral derivative; AggIn: aggressive index; FC: fuel consumption)

2 Related works

This work is based on several existing sources, including VTD, the standard driving cycle test

FTP-72 of city roads, the auto-encoder, and our previous work such as the model-based normalization approach and the aggressiveness index.

2.1 Vehicle test data (VTD)

VTD was collected by the Ford Motor Company from different drivers in four cities (Beijing, Shanghai, Chongqing, and Nanjing). The data collection equipment, i.e., Kvaser, was installed in the same kind of vehicle (Kuga 1.6 and 2.0) with the same vehicle setting (i.e., similar vehicle load, A/C, etc.). The travel route is mostly on the way to and from work. Many quantities are included in VTD, such as the engine speed, brake pressure (BP), throttle position (TP), and vehicle speed (VS). Generally, the pedal signals are the most direct factor affected by a driver, and thus they are critical for the modeling and evaluation of the driving behaviors. Since BP is seldom used during driving, the TP signal is considered as the main factor in this study.

In total, VTD samples from 178 drivers were used, including 18 drivers with style labels (mild, moderate, and aggressive, six drivers for each), 160 drivers with city labels, i.e., Shanghai, Beijing, Chongqing, and Nanjing, with a time resolution of 0.1 s and a total distance of 1080 km for each sample. The driving styles were labeled by experts and researchers from the Ford Motor Company based on drivers' operation of gas and brake pedals, i.e., TP and BP. For simplicity, the 18 style-labeled drivers are denoted as Mild1 to Mild6, Moder1 to Moder6, and Aggr1 to Aggr6. In addition, the vehicle type and city are denoted in a simpler way; e.g., Kuga 2.0 L in Shanghai is denoted as SH (2.0).

2.2 Federal test procedure 72 (FTP-72)

To reveal the driving characteristics under different city road types, in this study we use the urban driving cycle FTP-72 (Fig. 2). The transient cycle (FTP-72) represented by the US Federal Test Procedure (FTP) was used widely by several countries as a test procedure for certifying vehicle emissions in 1972. It consists of two phases, the cold start transient phase (0 to 505 s) and the stabilized phase (505 to 1370 s), which is very close to real-world driving.

2.3 Auto-encoder (AE)

AE is a neural network capable of creating efficient sparse representations of the input data in an unsupervised way (Baldi, 2012; Tschannen et al., 2018). A typical AE consists of two parts: the encoder and the decoder (Fig. 3). The input and output layers are connected by one or more hidden layers, where the output layer has the same number of nodes (neurons) as the input layer. Instead of predicting target value T for given input X, the AE is generally used to reconstruct its inputs by minimizing the difference between the input and the output.

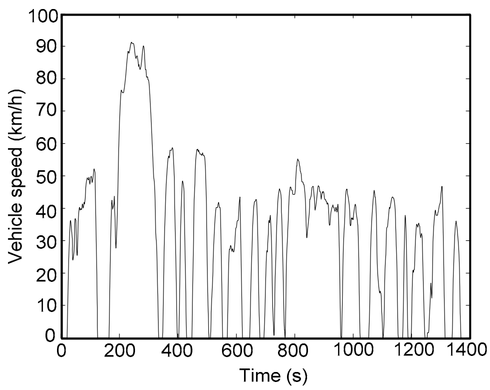

Fig. 2 The FTP-72 driving cycle

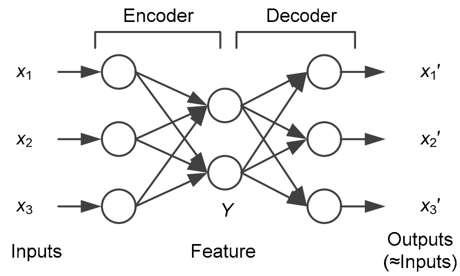

Fig. 3 Basic structure of an auto-encoder

Considering a data sample X with n samples and m features, the output of the encoder represents the feature or the reduced representation of X, denoted as Y. The feature contains as much information as the original data since it could accurately reconstruct the input. Thus, the feature could be used for image classification or other recognition tasks, and its great efficiency is validated against traditional approaches such as PCA (Tschannen et al., 2018).

Then the decoder is tuned to reconstruct the original dataset X from the encoder's representation Y by minimizing the difference between X and X'.

Specifically, the encoder is a function f that maps the input X to feature Y. The process can be represented by

$$Y = f(X) = s_f(WX + b_X), \tag{1}$$

where s_f is a nonlinear activation function. The encoder is parameterized by a weight matrix W and a bias vector $b \in \mathbb{R}^n$. If the nonlinear activation function is not added, then AE has no essential difference from the ordinary PCA.

Similarly, the decoder function maps hidden representation Y back to a reconstruction X':

$$X' = g(X) = s_g(WX + b_Y), \tag{2}$$

where s_g is a nonlinear activation function. The decoder's parameters are a bias vector b_y and matrix W'.

Since the goal of training an AE is to reconstruct the output X' to be as consistent as the input X, the task is equivalent to finding parameters θ=(W, b_X, b_Y) by which the reconstruction loss is minimized on the given input X. The objective loss function is given as

$$\Theta = \min_\theta L(X, X') = \min_\theta L\left(X, g(f(X))\right). \tag{3}$$

Different forms of the loss function are used for linear and nonlinear reconstruction. For linear reconstruction, the loss function L_1 is defined as

$$L_1(\theta) = \sum_{i=1}^{n} \|x_i - x_i'\|^2 = \sum_{i=1}^{n} \|x_i - g(f(x_i))\|^2. \tag{4}$$

For nonlinear reconstruction, the loss function L_2 is given in the form of cross-entropy as

$$L_2(\theta) = -\sum_{i=1}^{n} \left[x_i \lg y_i + (1-x_i)\lg(1-y_i)\right], \tag{5}$$

where $x_i \in X$, $x_i' \in X'$, and $y_i \in Y$.

2.4 Model-based normalization

A model-based normalization scheme was proposed in our previous work (Shi et al., 2015b). The normalization process is illustrated in Fig. 4. Raw driving behavior is normalized by conducting the virtual driving cycle test. A personalized driver model is first established using the real-world VTD of a certain human driver, and then employed as the virtual driver to conduct a speed-following task as defined by the standard driving cycle test, e.g., FTP-72. A proportional-derivative (PD) controller is employed as an auxiliary controller to improve the transient response. A desired speed at time t, $VS^*[t]$, is abstracted from FTP-72 speed profile to serve as an input to the driver model and the auxiliary controller; the final control signal, TP[t], or BP[t], is the summation of the outputs of the driver model and the auxiliary controller. The plant could be a real vehicle, a dyno, or a vehicle model.

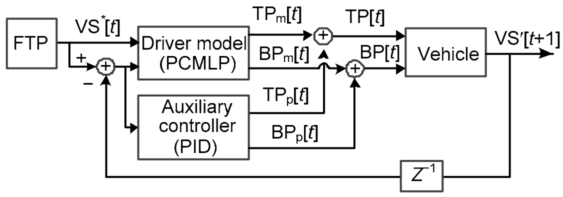

Fig. 4 Model-based normalization (FTP: federal test procedure; VS: vehicle speed; TP: throttle position; BP: brake pressure)

In this way, the raw driving behavior is normalized by conducting the virtual driving cycle test. This approach is effective for normalizing the driving behavior, but it is somewhat complicated and time-consuming because of the need to establish and train the driver model and to conduct the virtual driving cycle test.

2.5 Aggressiveness index

In our previous study (Shi et al., 2015b), A^*_{SESD} was proposed and validated as an index for the aggressiveness and driving style classification based on TP signals. It is the average of energy spectrum density (ESD) of normalized TP with respect to the error between the desired and actual VSs. These quantities are defined by

$$A_{\text{SESD}} = \text{Average(ESD(TP))}, \tag{6}$$

$$A^*_{\text{SESD}} = A_{\text{SESD}} / \text{std(error)}, \tag{7}$$

where error stands for the difference between the desired and actual speeds, std means the standard deviation, A_{SESD} is the average of std of the normalized TP. For simplicity, A^*_{SESD} is used as the aggressiveness index (AggIn) in this study. This is the ESD of the normalized TP with respect to the error between the desired and actual VSs.

3 GAE-based normalization of the driving behavior

The normalization process can be considered as the mapping of the driving behavior for conditions in a many-to-one manner. Hence, this task might be accomplished using AE when following a standard speed profile. To ensure positive correlation between the vehicle speed and the driving operation, we propose to impose a gate constraint between the encoder and decoder to form a gAE.

3.1 Gated auto-encoder (gAE)

TP and VS should be positively correlated during driving; i.e., TP should be positive when accelerated and be zero when not accelerated. As mentioned, to ensure this positive correlation, we propose to place a gate constraint between the decoder and encoder in the symmetric structured AE. gAE is illustrated in Fig. 5, where a gate function is placed after the feature layer. The gate function is defined as follows:

$$\begin{cases} \text{gate}(x)=\begin{cases} x, & x=\text{VS}, \\ \text{ReLU}(a)\otimes\text{ReLU}(x), & x=\text{TP}, \end{cases} \\ \text{ReLU}(y)=\begin{cases} 0, & y<0, \\ y, & y\geq 0, \end{cases} \end{cases} \tag{8}$$

where a is the acceleration, and $\otimes$ denotes the element-wise product. The rectified linear unit (ReLU) is an activation function used widely in neural networks. It is employed in this study because it works better than the tanh unit (Krizhevsky et al., 2012).

3.2 gAE-based normalization

The objective of driving behavior normalization is to provide a fair basis for evaluation by mapping driving behaviors in different situations to an identical one. The FTP-72 driving cycle is used here as the standard speed profile.

Adopted from VTD, VS and TP are the inputs to gAE, the gated features (v and tp) are the normalized result, and VS′ and TP′ are the outputs of gAE. During the training process, v is required to be as close as possible to the speed curve of FTP-72. The differences between the original driving behaviors (VS and TP) and the reconstructed driving behaviors (VS′ and TP′) are propagated backward layer by layer to adjust the parameters of gAE.

In the above way the loss function of gAE is redesigned in consideration of the aforementioned factors. The loss function is

$$\begin{aligned} \text{Loss}=\alpha\frac{1}{N}\sum_{n=1}^{n}(\text{VS}_n-\text{VS}'_n)^2+\beta\frac{1}{N}\sum_{n=1}^{n}(\text{TP}_n-\text{TP}'_n)^2 \\ +\gamma\frac{1}{N}\sum_{n=1}^{n}(v-V_\text{F})^2, \end{aligned} \tag{9}$$

where V_F denotes FTP-72. The above loss function consists of three parts, and each has its own coefficient. The first two parts are designed to minimize the errors of the input and the output. The last part is to constrain the vehicle to run at the desired speed, i.e., the FTP-72 driving cycle. In this study, the three coefficients (α, β, γ) are set to α=1.0, β=1.0, and γ=1.0 because of their equal importance, and the model is optimized by the Adam optimizer. The above

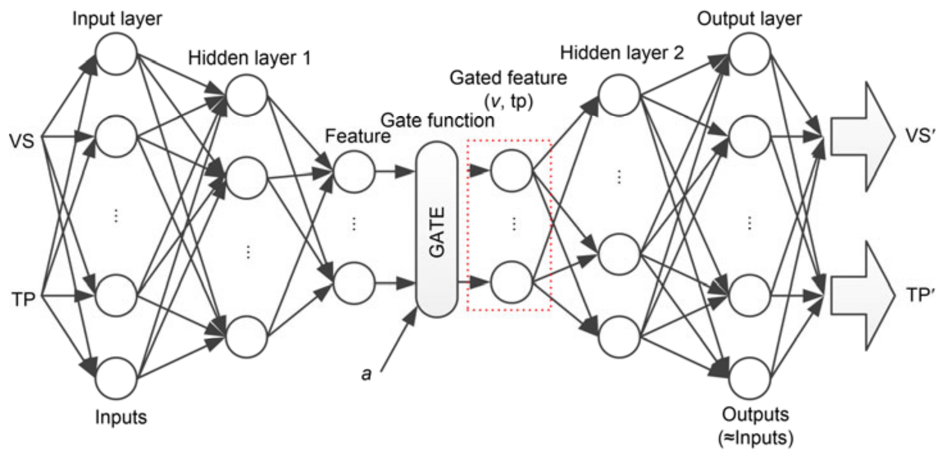

Fig. 5 Basic structure of the gated auto-encoder (gAE)

procedures are conducted on the VTD samples until the loss function stabilizes to the goal, which is set to 0.001 here. The gated features v and tp at this moment are regarded as the normalization results of the driving behavior.

4 Simulations

To verify the effectiveness of the proposed scheme, simulations were conducted to study three important issues, i.e., consistency with the model-based approach, applications to quantitative evaluation of the driving behavior, and detection of abnormal driving. In total, the VTD samples from 178 drivers were used, including 18 drivers with style labels (mild, moderate, and aggressive, six drivers for each), 160 drivers with city labels, i.e., Shanghai, Beijing, Chongqing, and Nanjing. For simplicity, normalized TP and raw TP are denoted as nTP and rTP, respectively.

4.1 Model performance

In the simulations, the normalization was conducted via gAE by mapping driving behaviors, in different situations, to an identical one, i.e., the FTP-72 driving cycle. Fig. 6a shows the mapping speed of an aggressive driver and the FTP-72 cycle, while Fig. 6b illustrates the speed error between them. It can be seen from Fig. 6a that the gAE model was well able to accomplish the normalization task, and that the majority of speed errors was controlled in the interval of [−0.5, 0.5] m/h.

The model loss function against the number of iterations for an aggressive driver is shown in Fig. 7. In the simulation, the loss function of the proposed gAE-based normalization could stabilize to the goal (set at 0.01 in this work) within 200 iterations.

The statistics of different model structures are listed in Table 1. When the model went deeper with more hidden layers, more iterations were needed to reach stabilization. As shown in Table 1, when the model had two hidden layers, the model could stabilize within 200 iterations and the final loss was 0.0085. When the model had four hidden layers, the final loss of the model was improved by about only 0.0002. In consideration of both computational burden and efficiency, the number of hidden layers was set at two.

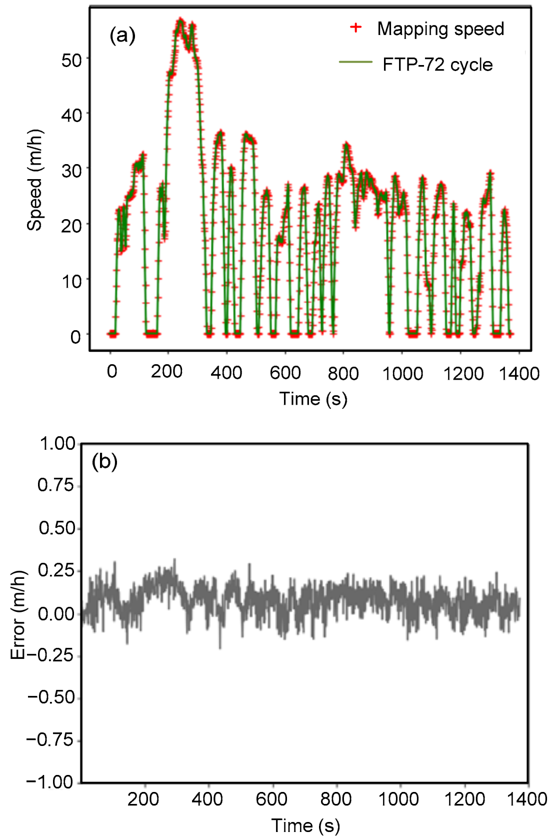

Fig. 6 Normalization of Aggr1: (a) mapping speed and FTP-72; (b) error between the mapping speed and FTP-72

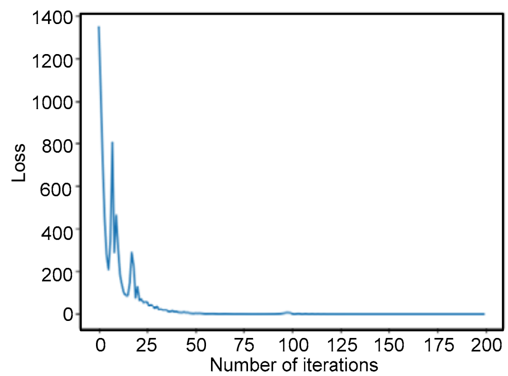

Fig. 7 Model performance assessment: model loss function against the number of iterations for an aggressive driver

Table 1 Comparison of training time and running time among different approaches

Number of hidden layers	Number of iterations	Final loss
2	100–200	0.0085
4	150–400	0.0083
6	300–600	0.0089

4.2 Normalized behaviors using the model- and gAE-based approaches

The gAE-based approach was applied to the 18 VTD samples of three styles to test its normalization performance. The model-based approach was applied to the same VTD samples for comparison. Figs. 8–10 show examples of the raw driving behavior (denoted as rTP) and the normalized one (denoted as nTP) using the gAE-based approach. The corresponding VS and the FTP-72 speed profile are presented as a reference.

As shown in Figs. 8–10, nTP showed a great difference from rTP when the driving behavior was normalized under the reference speed profile of FTP-72, but it was generally in conformity with the original driving style; i.e., larger acceleration led to larger TP, and the more aggressive the driver is, the fiercer the TP operations are.

4.3 Quantitative evaluation of driving styles

The driving behavior may be quantitatively evaluated by calculating AggIn. AggIn was computed on both rTP and nTP of the 18 drivers with three driving styles. The rTP of VTD was normalized using both the gAE- and model-based approaches. Examples of rTP and nTP of the gAE-based method are presented in Figs. 8–10 and Table 1.

Figs. 11–13 present AggIn of rTP and nTP resulting from both the model- and gAE-based approaches. Each point on the same folded line represents a driver of the same style, e.g., Aggr1, Aggr2, …. Generally speaking, larger AggIn means more aggressive, and "closer to 0" means milder. The K-means algorithm was applied to the AggIn of 18 drivers. The dashed lines from top to bottom in Figs. 11–13 illustrate the clustering centers of aggressive, moderate, and mild styles, respectively.

As shown in Fig. 11, rTP had difficulty in correctly distinguishing driving styles of drivers 1, 2, and 3 because of the overlap in AggIn. This problem can be solved using the normalization of the driving behavior. As shown in Figs. 12 and 13, driving styles of the six drivers can be classified correctly using the nTP resulting from both the model- and gAE-based approaches. This verifies that the normalization is necessary for correct evaluation of the driving

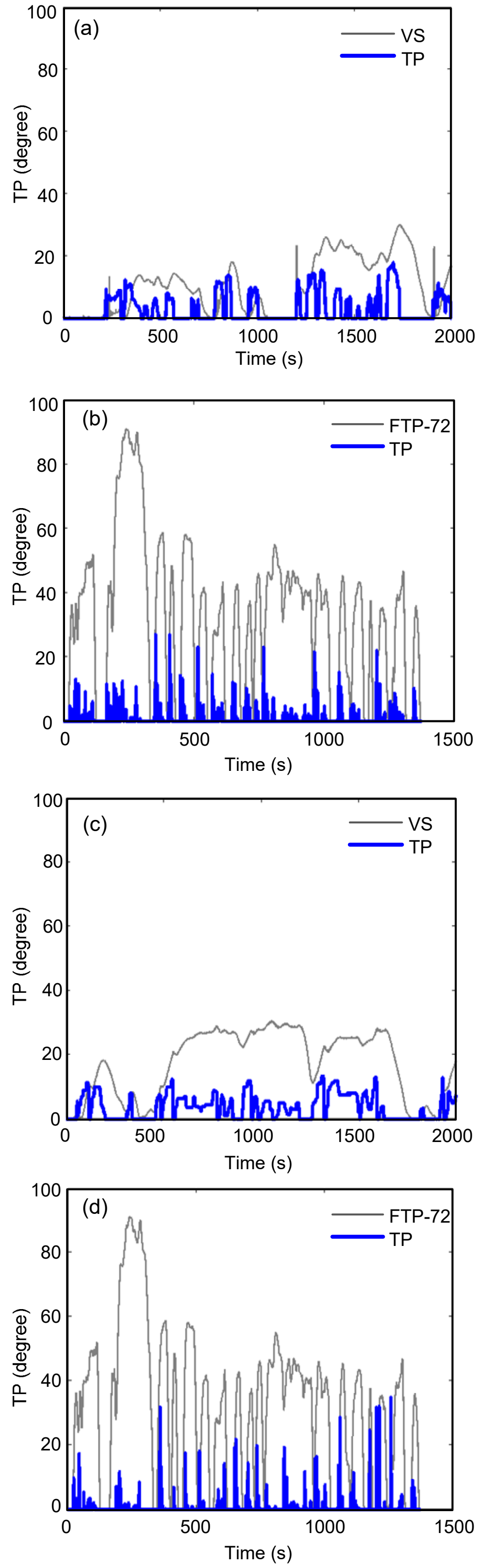

Fig. 8 Driving behaviors of the mild style: (a) rTP, Mild1; (b) nTP, Mild1; (c) rTP, Mild2; (d) nTP, Mild2

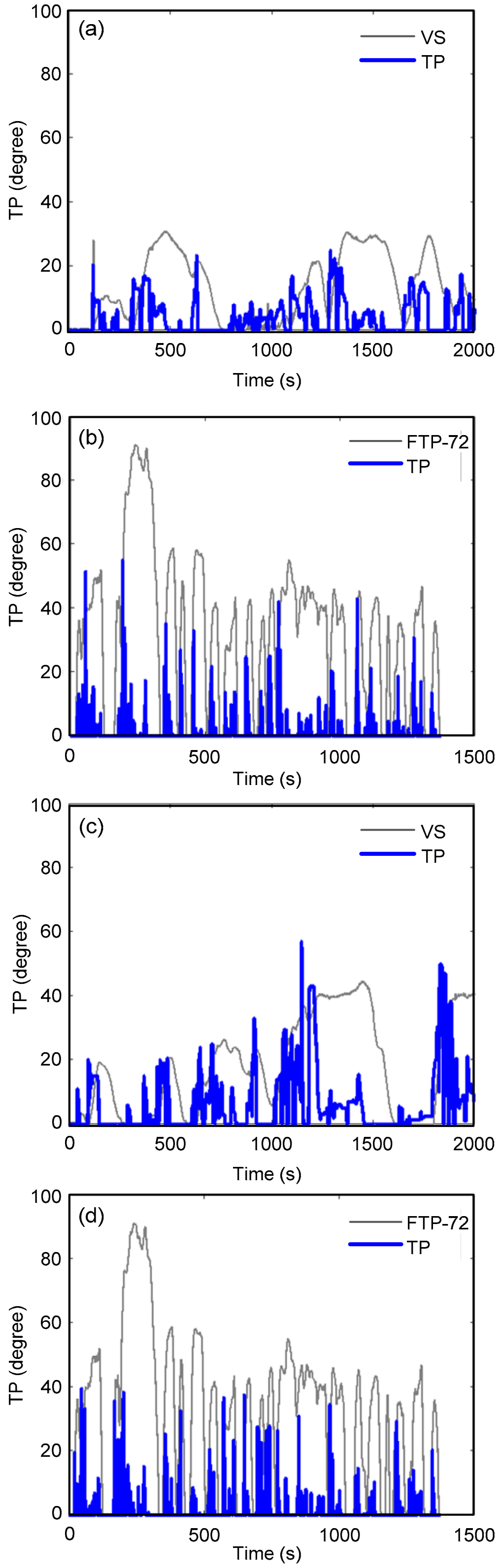

Fig. 9 Driving behaviors of the moderate style: (a) rTP, Moder1; (b) nTP, Moder1; (c) rTP, Moder2; (d) nTP, Moder2

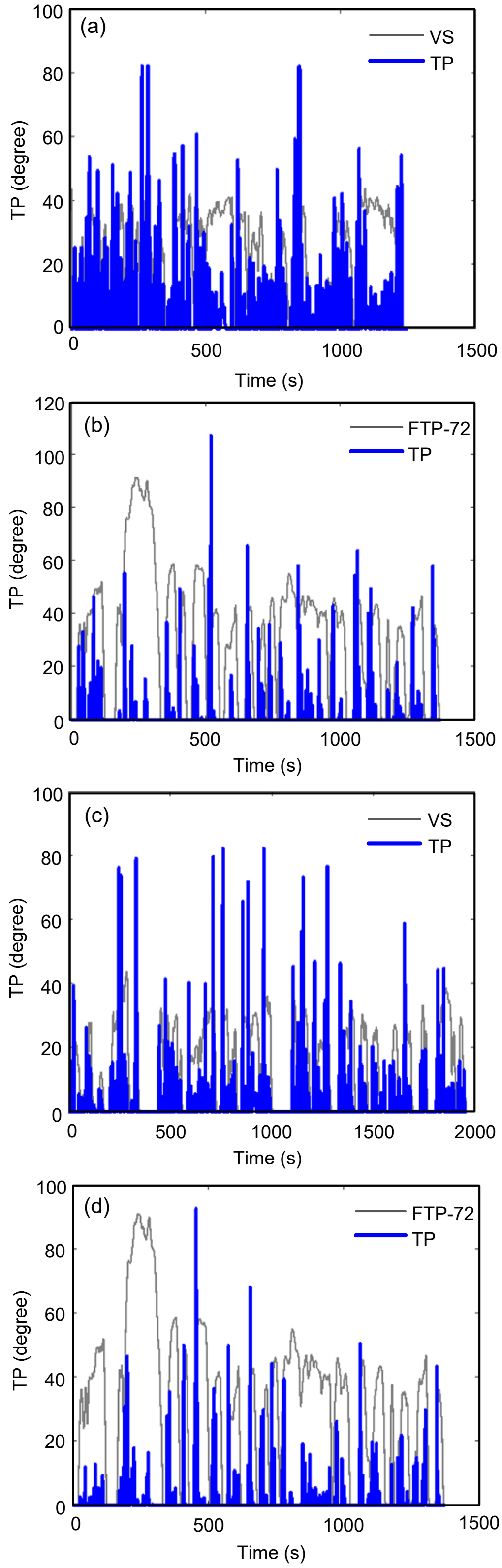

Fig. 10 Driving behaviors of the aggressive style: (a) rTP, Aggr1; (b) nTP, Aggr1; (c) rTP, Aggr2; (d) nTP, Aggr2

behavior, and the consistency between the gAE- and model-based approaches is thus demonstrated. The detailed indices of Figs. 11–13 are summarized and presented in Table 2.

According to the bar chart of clustering centers (Fig. 14), we can see that there existed greater diversity among the bars of the gAE-based method than among those of the model-based method. More quantitative statistics are presented in Table 3, where the coefficient of variation (CV) was employed to measure the dispersion of a distribution with respect to the aforementioned approaches:

$$CV=\sigma/\mu, \tag{10}$$

where σ is the standard deviation and μ is the mean of the distribution.

As shown in Table 3, the gAE-based method had a much larger CV than the model-based method. Statistics on CV indicated that the AggIn of the

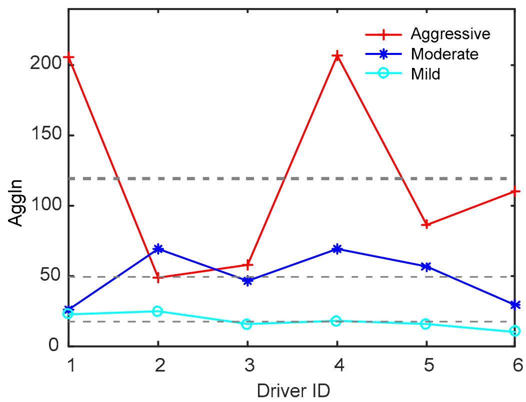

Fig. 11 AggIn of rTP for raw data

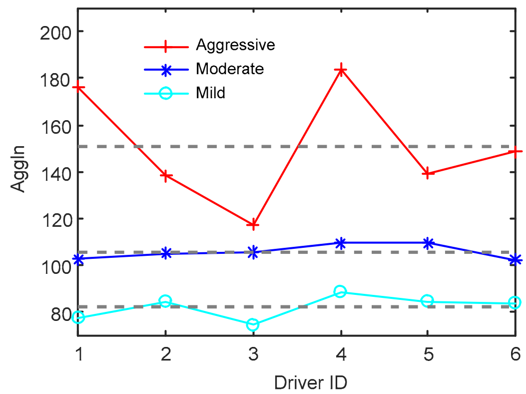

Fig. 12 AggIn of nTP for the model-based approach

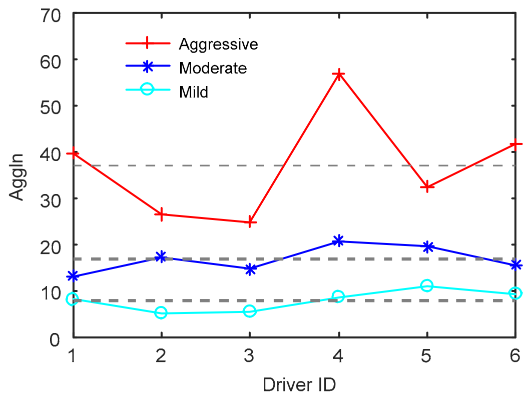

Fig. 13 AggIn of nTP for the gated auto-encoder based approach

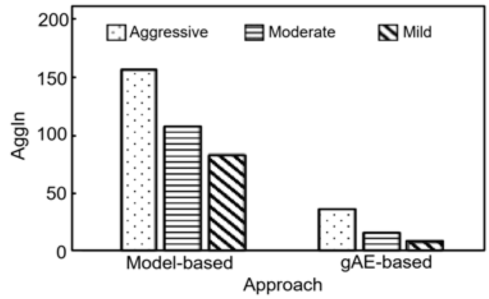

Fig. 14 Average AggIn resulting from the model- and gAE-based approaches

Table 2 AggIn of the normalized driving behavior using the two approaches

Driver	Raw data	AggIn	
		Model-based	gAE-based
Aggr1	205.20	176.25	39.87
Aggr2	49.01	138.32	26.63
Aggr3	57.76	117.36	25.05
Aggr4	206.79	183.64	56.93
Aggr5	86.86	139.35	32.60
Aggr6	110.21	148.42	41.75
Moder1	25.80	102.64	13.30
Moder2	69.12	104.91	17.44
Moder3	46.68	105.49	14.76
Moder4	69.32	109.33	20.95
Moder5	56.40	109.27	19.69
Moder6	30.11	102.13	15.62
Mild1	23.15	77.41	9.24
Mild2	24.78	84.37	5.29
Mild3	15.46	74.27	5.61
Mild4	17.67	88.49	8.80
Mild5	15.79	84.47	11.14
Mild6	10.78	83.72	9.47

Table 3 The coefficient of variation (CV) on the two normalization methods

Approach	CV
Model-based	0.3213
gAE-based	0.7181

gAE-based method had a more dispersed distribution, which can lead to better classification ability.

4.4 Comparisons with other methods

We compared the proposed gAE method with the convolutional neural network (CNN), variational auto-encoder (VAE), and generative adversarial network (GAN) to conduct the same normalization task on the same platform (GeForce GTX 2060Ti). Evaluation indices including precision (P), recall (R), and F1_score (F1) were used to indicate the performance of classifying different driving styles, and can be expressed as

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \tag{11}$$

$$R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \tag{12}$$

$$\mathrm{F1} = \frac{2PR}{P + R}, \tag{13}$$

where the class of interest is denoted as positive, while the others are negative. The positive one predicted as positive is called "true positive (TP)," while the positive one predicted as negative is called "false negative (FN)." Moreover, the negative one predicted as positive is called "false positive (FP)," and the negative one predicted as negative is called "true negative (TN)."

The detailed results are shown in Table 4. The approaches were used to normalize the raw driving behavior separately. Then the normalized TP signal was adopted to calculate AggIn, which was further used in the driving style classification task via the K-means algorithm. As shown in Table 4, the other methods can provide a performance of at least 82%. In contrast, our proposed solution outperformed other methods, and can be more accurate to meet industry needs.

Table 4 Comparison of indices for the proposed method and other approaches

Approach	Precision	Recall	F1_score
gAE	**0.98**	**0.96**	**0.97**
CNN	0.90	0.88	0.89
VAE	0.93	0.95	0.94
GAN	0.82	0.83	0.82

gAE: gated auto-encoder; CNN: convolutional neural network; VAE: variational auto-encoder; GAN: generative adversarial network. The best results are in bold

In addition, both the training and testing times for these approaches are illustrated in Table 5. Compared with the listed algorithms, our proposed method can achieve better performance with affordable training and testing time.

Table 5 Comparison of training time and running time among different approaches

Approach	Training time (min)	Testing time (s)
gAE	**16.53**	**2.37**
CNN	56.28	3.74
VAE	79.68	2.51
GAN	95.21	3.32

gAE: gated auto-encoder; CNN: convolutional neural network; VAE: variational auto-encoder; GAN: generative adversarial network. The best results are in bold

5 Conclusions

An efficient approach for normalizing driving behaviors was proposed using an AE. We implemented the normalization by mapping the driving behaviors in different situations to an identical one. A gate constraint was imposed in between the decoder and the encoder in AE to ensure positive correlation between the inputs. The normalized driving behavior was applied to quantitative evaluation tasks, i.e., driving style classification using an aggressiveness index and fuel consumption comparison using a fuel consumption index. Results showed that the proposed scheme is consistent with the model-based approach and much easier and more efficient for driving behavior normalization. In the driving style classification task, the normalized driving behavior based on the proposed method obtained at least 95% accuracy and outperformed the other methods. Thus, the proposed approach is valuable for driving behavior analysis.

In future work, the proposed method might be applied to hybrid or autonomous vehicles. Also, online calibration of the driving behavior might be considered based on the normalized data.

Contributors

Xin HE designed the research. Zhe ZHANG and Jiapei YU processed the data. Xin HE and Li XU drafted the paper. Zhe ZHANG helped organize the paper. Xin HE and Li XU revised and finalized the paper.

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Compliance with ethics guidelines

Xin HE, Zhe ZHANG, Li XU, and Jiapei YU declare that they have no conflict of interest.

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