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• **Supplementary File** •

Car-following behavior modeling driven by small data sets based on mnemonic Extreme Gradient Boosting framework

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Appendix A Parallel Comparison

Compared with other models trained by small data sets, feedforward neural networks: back propagation (BP) neural network, radial basis function (RBF) neural network, generalized regression neural network (GRNN) and two types of recursive neural networks: Elman neural network, long short-term memory (LSTM). Parameters of the algorithms are shown in the Table below.

Table A1 Parameters of the algorithms.

Algorithm	Layer Structure (Neurons and Activation Functions)	Epochs
BP	Hidden layers:3; [60,200,60][sigmoid, tanh, linear]	1000
RBF	Hidden layer:1; Spread:0.1	200
GRNN	Pattern Layer:1 + Summation Layer:1; Spread:0.1	250
Elman	Hidden layers:3 + Receiving Layer:1; [10,20,1][tanh, sigmoid, linear]	1000
LSTM	Sequential models, Time steps:10; [LSTM, Dropout, LSTM, Dropout, Linear]	600

Trained by the same data sets, the comparison of results is shown in Figure A1, and the corresponding R^2 values are shown in Figure A2. It can be seen that the abnormal fluctuations of the predicted results not only appear in the XGBoost model, but also have a certain reflection in the commonly used Feedforward Neural Networks (BP, RBF, GRNN) models. Compared with the XGBoost model and the Feedforward Neural Networks models, the predicted results of the Recursive Neural Networks models are smoother, and there are fewer abnormal fluctuations. Also, it can be found in Figure A1 that the overall prediction accuracy (R^2) of Recursive Neural Networks models are higher than other models, which reflects that the Recursive Neural Networks has a better learning ability for the naturalistic driving data. As for the models trained by small data sets, there are distinct differences in different algorithms, among them, the XGBoost is significantly better at few shot learning, and the advantages of Recursive Neural Networks are reflected in the learning of naturalistic driving data.

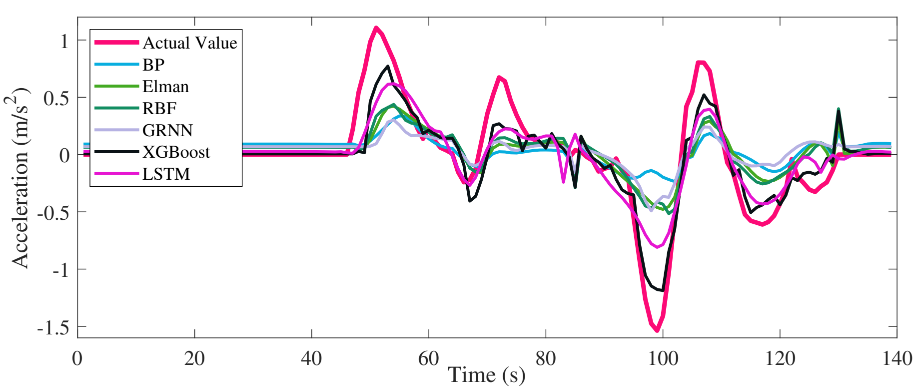

Figure A1 The comparison of prediction results.

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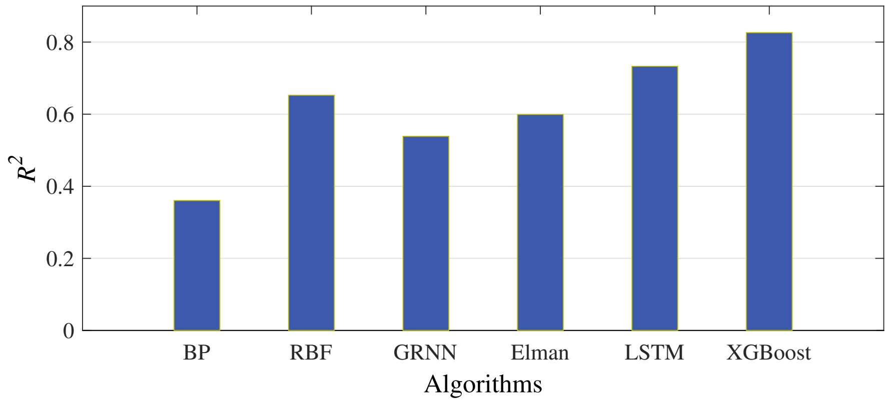

Figure A2 The comparison of prediction accuracy.

In addition, it can be found that the essential defects of XGBoost in establishing data-based car-following model. The prediction of car-following characteristic is essentially a time series issue, considering the real driving state of drivers, the actions of the previous moment will have a great impact on subsequent operations. However, as an algorithm based on the Gradient Boosting Decision Tree (GBDT) [1], in the process of learning and modeling, the XGBoost does not take into account the autocorrelation and the misalignment of time series. Compared with Recursive Neural Networks (Elman and LSTM), it has no independent memory functions, which reduces the upper limit of this algorithm for handling the time series issues. This defect directly causes the irregularities and fluctuations of the XGBoost model.

The XGBoost has no essential advantage on the time series issues such as car-following predictions, but relying on the excellent few shot learning ability, it still has a pretty good performance in the previous research, as shown in Figure 8. This also gives us great confidence to investigate XGBoost further. In order to remedy its limitation on the memory of time series, we add the memory units of Recursive Neural Networks to the XGBoost framework. Meanwhile, physical constraints are considered according to the real driving experience. The following research is based on this improved XGBoost framework, called Mnemonic XGBoost or M-XGBoost.

Appendix B Personalized Dynamic Constraints

The constraint of driving safety can avoid the potential safety hazards caused by prediction errors [2], the main parameters of this constraint are the minimum acceptable following distance d_{min} and the minimum acceptable braking time t, the constraint is shown as follows.

$$a \leqslant 2\frac{\Delta s - d_m in - v_i t}{t^2} \tag{B1}$$

The energy consumption is proportional to the acceleration and the jerk of the vehicle [3], the main parameters of this constraint are the current acceleration a_f, the current jerk j_f, the constraint is shown as follows.

$$\begin{cases} a_{f,min} \leqslant a_f \leqslant a_{f,max} \\ j_{f,min} \leqslant j_f \leqslant j_{f,max} \end{cases} \tag{B2}$$

The driving comfort is also proportional to the acceleration and the jerk of the vehicle [4]. The goal of expected following distance is also required, which is shown as follows. The main parameters of this constraint are the proportionality coefficient c and the expected following distance d_e.

$$When \Delta s > d_e, a = ca_i \tag{B3}$$

The constraints used in this paper are implemented by the algorithm shown as follows.

Algorithm 1: Personalized Dynamic Constraints

Input: a_i, predicted acceleration of the rear car
Δs, current distance
Input: $a_{\max}$, maximum acceleration; $b_{\max}$, maximum breaking acceleration
j_+, maximum jerk; j_-, minimum jerk
Input: $d_{\min}$, minimum acceptable following distance
t, minimum acceptable braking time
d_e, expected following distance
c, proportionality coefficient

```
Δt ← 1                                  // sampling frequency (1Hz)
if   a_i ≤ b_max                         // acceleration constraints (fuel & comfort)
     a_i1 ← b_max
         elseif   a_i ≥ a_max
                  a_i1 ← a_max
end
if   a_i ≤ a_i-1 + j-Δt                  // jerk constraints (fuel & comfort)
     a_i1 ← a_i-1 + j-Δt
         elseif   a_i ≥ a_i-1 + j+Δt
                  a_i1 ← a_i-1 + j+Δt
end
if   a_i ≥ 2(Δs − d_min − v_i t)/t^2      // safe distance constraint (safety)
     a_i1 ← 2(Δs − d_min − v_i t)/t^2
end
if   a_i ≥ 0 & Δs ≥ d_e                  // expected distance constraint (comfort)
     a_i1 ← c a_i
end
```

Output: a_{i1}, current acceleration of the rear car

Figure B1 Personalized dynamic constraint algorithm.

Appendix C M-XGBoost Verification

The predicted results of the XGBoost, LSTM, the M-XGBoost and constrained M-XGBoost models are compared with the actual value, as shown in Figure C1. Assume that the driver want to follow the front car comfortably and safety, and maintain a relative distance of 60 m. With the goal of this, the personalized dynamic constraints are verified in this part. The constraint items used in this part are as mentioned in Figure B1. The constraint parameters adjusted for this goal are shown in Table C1, j_+ is the maximum jerk, j_- is the minimum jerk, a_{max} is the maximum acceleration, b_{max} is the maximum breaking acceleration, t is the minimum acceptable braking time, d_e is the expected following distance and c is the proportionality coefficient.

Table C1 Expected constraint parameters.

a_{max}	b_{max}	j_+	j_-	t	d_e	c
$2.5m/s^2$	$-5m/s^2$	$0.25m/s^3$	$-0.2m/s^3$	$1.5s$	$60m$	2

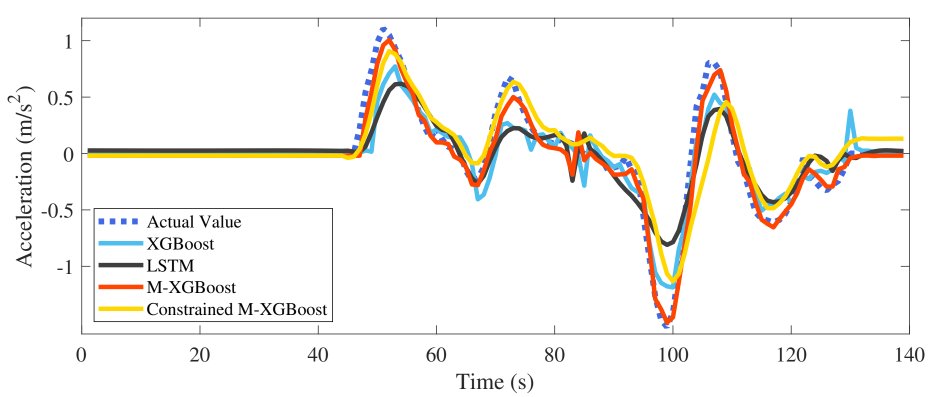

Figure C1 The comparison of models prediction results.

Table C2 The comparison of prediction accuracy.

Model	$RMSE$	MAE	R^2
XGBoost	0.1760	0.1091	0.8262
LSTM	0.2181	0.1370	0.7330
M-XGBoost	0.0941	0.0608	0.9503
Constrained M-XGBoost	0.2136	0.1345	0.7439

It can be seen from the evaluation indicators, shown as Table C2, the $RMSE$ of the M-XGBoost is reduced by 46.5%, the MAE is reduced by 44.0%, and the R^2 is increased by 15%. It can be seen that, compared with the prediction result of the original M-XGBoost, after the constraint process the peaks and troughs of the results are reduced, and shown as the indexes ($RMSE$, MAE, R^2), compared with the results of original M-XGBoost, the constrained results are not good at fitting the actual value, but the overall trend of it is smoother. Meanwhile, the transition state (50-90s) of constrained results are increased to counteract the iteration errors, which prevents the relative distance become farther and farther. The personalized dynamic constraints ensure the coordination of car-following state and avoid the risk caused by prediction errors.

The method of trajectory reconstruction is used to verify the follow-up ability of the predicted results. Considering the time interval of the Cell (10s), the number of input samples should be a multiple of 10. In this paper, a straight-line following process 40-80 s of the test set is selected, and this process starts from the standstill. The trajectory reconstruction starts from 40 s, and the state parameters (relative velocity, relative distance and velocity) at this moment are initial values. The overall process is to iteratively calculate the state of the next moment based on the state of the current moment, the iterative process is shown as Equation C1 and Figure C2.

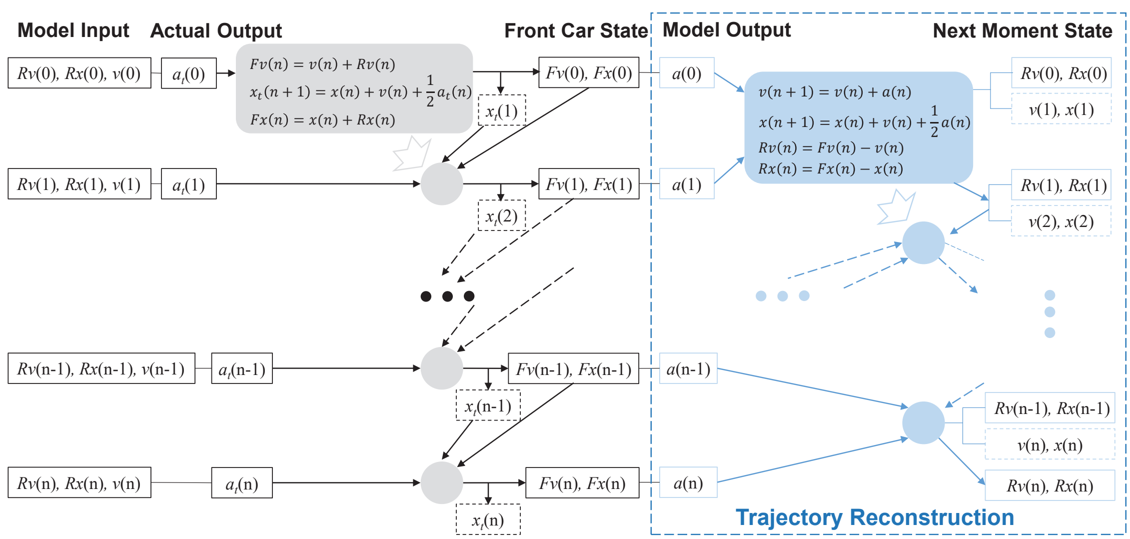

Figure C2 Trajectory reconstruction.

Furthermore, the reconstructed displacement results of these models are shown as Figure C3, the dashed line and solid lines indicate the displacement of the front car and rear car respectively. It can be seen that the following performance of constrained results is better than the original M-XGBoost. Within the range of 30-40 s, the displacement results of original M-XGBoost gradually deviates from the actual trajectory, the offset reaches about 50 m at the time of 40 s and it may increase further. This is caused by iteration errors generated from the car-following prediction. However, the iteration errors of constrained results are identified and counteracted by the personalized dynamic constraints. As previously assumed, shown as Figure C3, it maintains a proper following distance of about 60 m, which verifies the effect of personalized dynamic constraints.

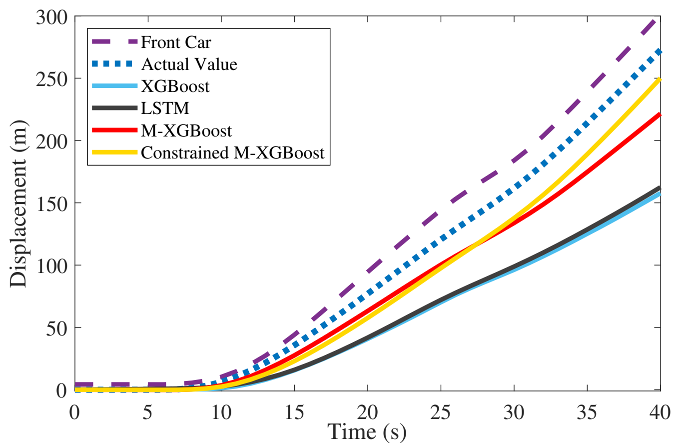

Figure C3 Reconstructed displacement.

The iteration parameters of the trajectory reconstruction [5] are shown in Figure C4. In the acceleration phase between 6 s and 28 s, as shown in Figure C4, the response of constrained results is slow, but there is a steady trend. After the time of 28 s, the deviation of original M-XGBoost results and actual value increases gradually, while the constrained M-XGBoost model achieves a 60 m following distance. It can be seen that the personalized dynamic constraints ensure the stable of car-following process. Compared with the original M-XGBoost, although the constrained results have some offset with the actual value, it improves the accuracy of trajectory tracking. Also these results reflect a different driving style (following distance 60 m) from the actual value (following distance 30 m), which achieves the switching of driving styles based on the M-XGBoost model trained by a small data set.

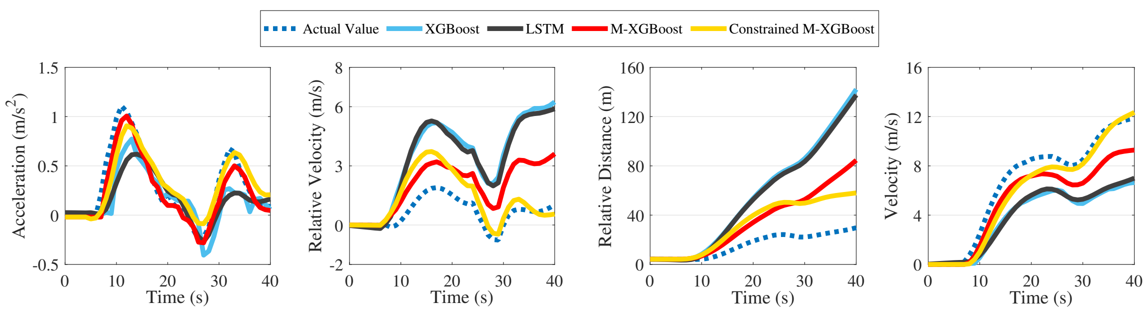

Figure C4 The comparison of reconstructed parameters.

Shown as Figure C4, the constrained results reached the first peak at 16 s, then the offset between the constrained results and actual value gradually decreases, eventually overlapping with the real value because of the delay. Also, after the time of 16s, in order to catch the actual value, the constrained model needs to increase its velocity quickly, but limited by the constraint of maximum jerk. Except for the delay, the whole process basically accords with the driver behavior. This phenomenon is more intuitively represented in the parameter of jerk [6], shown as Figure C5, and the comparison of these models are shown as Table C3.

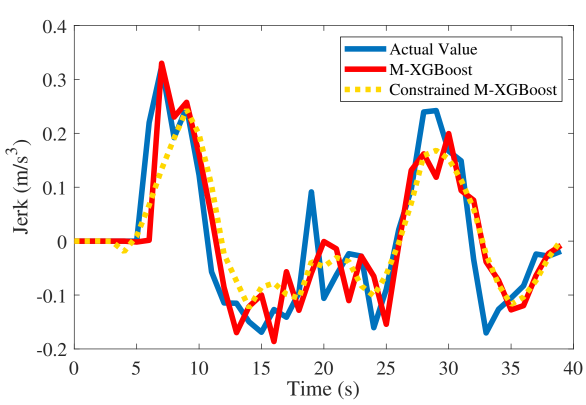

Figure C5 Reconstructed jerk.

Table C3 Evaluation indexes of the reconstructed jerk.

Model	$AbsoluteMean$	j_+	j_-	$Mean$	$Variance$
Actual Value	0.1035	0.3240	-0.1703	0.0021	0.1316
original M-XGBoost	0.0887	0.3300	-0.1862	0.0017	0.1194
Constrained M-XGBoost	0.0778	0.2437	-0.1236	0.0056	0.0982

It can be found from the Mean and the Variance of Table C3, the personalized dynamic constraints reduce the sharp changes of the jerk and make the following performance of M-XGBoost smoother. Although the constrained results have some offsets with the actual value, it can achieve the car-following goal set by constraints and reflect a better performance of car-following.

Generally, radical drivers and novice drivers consume more fuel than the ordinary drivers for the same displacement, which is mainly related to the sharp acceleration and deceleration during the driving. In order to verify the fuel consumption of the original M-XGBoost model and constrained M-XGBoost model, the energy consumption of the models are equivalent to the superposition of instantaneous power consumption from tires, the expression is shown as follows.

$$P_e = \frac{1}{\eta_T}(mgfv + mgiv + \frac{C_D A v^3}{1.63} + \zeta mva) \tag{C1}$$

This formula ignores the effect of slope on fuel consumption, the road slope coefficient i is 0. The remaining parameters are set according to the Table C4. Among them, the m is the weight of vehicle, g is the acceleration of gravity, v is the current velocity, a is the current acceleration, A is the windward area, η_T is the transmission efficiency, f is the coefficient of rolling resistance, ζ is the correction coefficient of rotating mass and C_D is the coefficient of air resistance.

Table C4 Vehicle parameters.

Parameter	Value	Unit
m	1580	kg
g	9.8	m/s^2
A	1.8	m^2
η_T	0.8	-
f	0.015	-
C_D	0.3	-
ζ	1.1	-

Based on the instantaneous power of driving, the fuel consumption of 0-40 s in this part can be calculated according to the Formula shown as follows. E is the total energy consumption and P_t is the instantaneous power at time t. The relationship between the displacement and the energy consumption of models in 40 second is shown in Figure C6. It can be seen that the following performance of constrained M-XGBoost model is better than the original M-XGBoost in the case of consuming same amounts of energy.

$$E = \sum_{t=1}^{n} P_t t \tag{C2}$$

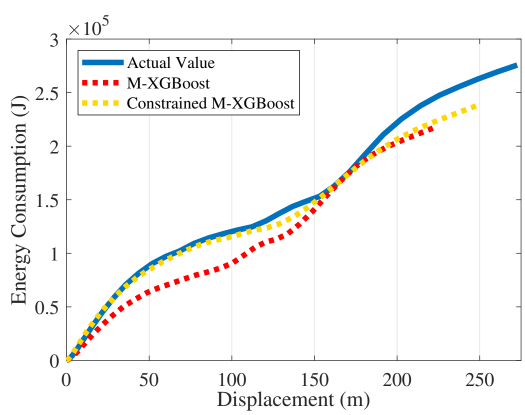

Figure C6 The relationship between energy consumption and the displacement.

References

1 Friedman J H. Greedy Function Approximation: A Gradient Boosting Machine. Ann Stat, 2001, 29(5): 1189-1232

2 Yu X, Liu L. Leader-follower formation of vehicles with velocity constraints and local coordinate frames. Sci China Inf Sci, 2017, 60(07): 81-95

3 Zhang J H, Li Q, Chen D P. Multi-objective adaptive cruise control with multi-mode strategy. J Univ Electron Sci and Technol China, 2018, 47(3): 368-375

4 Moon S, Yi K. Human driving data-based design of a vehicle adaptive cruise control algorithm. Veh Syst Dyn, 2008, 46(8): 661-690

5 Punzo V, Borzacchiello M T, Ciuffo B. On the assessment of vehicle trajectory data accuracy and application to the Next Generation SIMulation (NGSIM) program data. Transp Res Part C. 2011, 19(6): 1243-1262

6 Gasparetto A, Zanotto V. A technique for time-jerk optimal planning of robot trajectories. Mech Mach Theory, 2008, 24(3): 415-426