

Construction of an Accelerator Operation Prediction Model Based on Driving Data Clustering Considering Driving Characteristics

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Traffic-flow simulation requires driver models that reproduce human driving behavior. However, when the number of drivers is large, constructing an individual model for every driver is impractical. Therefore, this study classifies driving datasets based on accelerator-operation characteristics under comparable driving environments and constructs cluster-specific accelerator pedal position (APP) prediction models.

Twenty-seven public-road driving datasets from nine drivers and four vehicles were sampled at 10 Hz. Five variables—vehicle speed, vehicle acceleration, preceding-vehicle speed, preceding-vehicle acceleration, and inter-vehicular distance—were segmented into overlapping 30-sample windows. Each window was compressed into a 16-dimensional latent feature vector using an Long Short-Term Memory autoencoder(LSTM-AE). K-Means was then applied to the latent feature vectors to classify the time-series windows into ten driving environments. For each driving environment, the APP distribution of each dataset was represented by a normalized histogram with 1-percentage-point bins. The APP distributions of driving datasets i and j within the same environment were compared using the first-order Wasserstein distance $M_{ij}^{(k)}$. The final distance D_{ij} between driving datasets i and j was calculated using an environment weight $w_k = N_k \sigma_k$, defined by the number of samples N_k and the standard deviation of APP σ_k in each environment, as follows:

$$D_{ij} = \frac{\sum_{k \in \mathcal{K}_{ij}} w_k M_{ij}^{(k)}}{\sum_{k \in \mathcal{K}_{ij}} w_k}$$

where $\mathcal{K}_{ij}$ denotes the set of environments containing at least 101 APP samples in both datasets. The distances D_{ij} were calculated for all pairs of driving datasets to construct the final distance matrix: $D = [D_{ij}]$. A smaller element of D indicates that the corresponding two driving datasets exhibit more similar accelerator-operation characteristics. K-Medoids was then applied to the resulting distance matrix to classify the driving datasets into multiple clusters.

Finally, an LSTM-based APP prediction model was constructed for each cluster. The model used three input variables—preceding-vehicle speed, preceding-vehicle acceleration, and inter-vehicular distance—and predicted APP at the next time step from their histories over the most recent 30 samples.

The number of clusters was varied from $K = 2$ to $K = 7$. To ensure a fair comparison, matched random clusters were generated with the same cluster sizes and test datasets as the proposed clusters. Five random-cluster configurations were generated for each K , and each model was trained ten times using different random seeds. Prediction performance was evaluated using MAE, RMSE, and R^2 . Improvements were defined as random minus proposed for MAE and RMSE and as proposed minus random for R^2 ; thus, positive values favor the proposed method.

As shown in Fig. 1, positive mean improvements were obtained for all three performance metrics at every evaluated value of K .

To investigate the factors contributing to the reduction in the overall prediction error, the contribution of driving environment k to the overall MAE was defined as follows: $C_k = (N_k/N_{all})MAE_k$, where N_k/N_{all} is the proportion of test samples belonging to driving environment k , and MAE_k is the MAE within that environment. Because the sum of the contributions from all driving environments is equal to the overall MAE, C_k represents the portion of the overall prediction error attributable to the corresponding environment and reflects both its occurrence frequency and its environment-specific prediction error.

The analysis showed that the largest reduction in the MAE contribution occurred in a frequently observed medium-speed cruising environment. In this environment, driver-dependent differences in accelerator operation for maintaining speed—such as releasing, holding, or slightly depressing the accelerator pedal—tend to become evident. Therefore, the ability to group driving datasets with similar accelerator-operation characteristics in this environment was considered a major factor in the overall performance improvement. These findings demonstrate that clustering driving datasets based on accelerator-operation characteristics in different driving environments improves the accuracy of cluster-specific APP prediction. Future work will expand the dataset and evaluate whether the constructed models can reproduce realistic driving behavior in traffic-flow simulation.

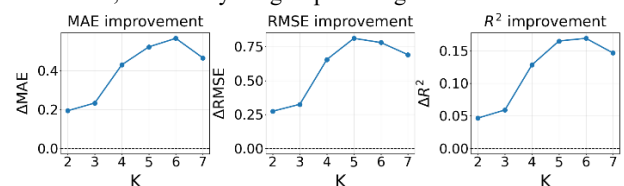


Fig. 1 Mean prediction performance improvements over random clustering for $K = 2 \sim 7$.