A Review of Driving Style Recognition Methods From Short-Term and Long-Term Perspectives

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***Abstract*—Driving style recognition provides an effective way to understand human driving behaviors and thereby plays an important role in the automotive sector. However, most works fail to consider the influence of deploying the recognition results on the vehicle side, which requires real-time recognition performance. To facilitate the application of driving styles in automotive, we survey related advances in driving style recognition along short- and long-term pipelines. We first defined short- and long-term driving styles and then described the input data used by the recognition models and related data-processing techniques. Furthermore, we also revisited existing evaluation metrics for different recognition algorithms. Finally, we discussed the potential applications of driving style recognition in intelligent vehicles.**

***Index Terms*—Driving style recognition, short-term and long-term, intelligent vehicles, evaluation metric.**

I. Introduction

As a commodity, intelligent vehicles must cater to consumers for better sales. A potential but clear direction for intelligent vehicles is from the original faster, more fuel-efficient direction to a more human-like and personalized direction [1] because drivers are apt to use the vehicle that behaves similarly to their operation, i.e., the more human-like, the more humans like [2], [3]. The prerequisite of making vehicles more human-like is understanding the driver's driving style. Many human-like or personalized functions can be created and added to intelligent vehicle systems by using learned driving styles [4].

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From the perspective of functionality, driving style is critical for autopilot systems, driving safety, energy conservation, emissions reduction, and driving assessment [5], [6], [7], [8], [9]. However, the data duration on which these applications are based is inconsistent. For example, human-like autonomous driving systems requires collecting a long period of driving data, and driver behaviour monitoring usually requires a short period of driving data. Thus, we divide driving style recognition into short-term and long-term driving styles towards various applications. *Short-term* driving style is mainly used to portray the way a driver operates the vehicle in a short period of time with a specific driving task. It is usually influenced by the current driving task and scenario, and thus is mainly used for driving behavior monitoring, correction [10], [11], and driver intention prediction [7], [12]. *Long-term* driving style portrays the way a driver operates the vehicle in a long period of time, which is usually obtained by analyzing long-term driving data. Long-term driving style does not depend on the driving scenario and is more stable than the short-term driving style. Thus, a long-term driving style is mainly used for the optimal design of advanced automotive systems [13] and autonomous driving systems to facilitate their promotion [14], [15].

From the perspective of hardware implementation, driving style recognition can be classified into short-term for an in-vehicle controller and long-term for a cloud computing platform. The in-vehicle controller requires low computing power and storage space [16] with a small amount of data but real-time computing, which is suitable for the short-term driving style. The cloud computing platform has a much more powerful computing performance and storage space and is thus suitable for long-term driving style [17], [18].

Some surveys or reviews focused on driving style recognition, but they failed to cover the existing driving style recognition algorithms, especially deep learning algorithms and implementation of driving style recognition. For example, Wang et al. [19] summarized the applications of driving style recognition to hybrid electrical vehicles (HEV) control strategies. Sagberg et al. [20] divided the application of driving style recognition into sevearal areas. Martinez et al. [5] systematically reviewed the work on driving style characterization and the design process of driving style recognition, and its application to intelligent vehicle control. To facilitate the implementation of driving style recognition, we review driving style recognition into short-term and long-term types, which guides researchers to choose a short- or long-term driving style recognition algorithm for

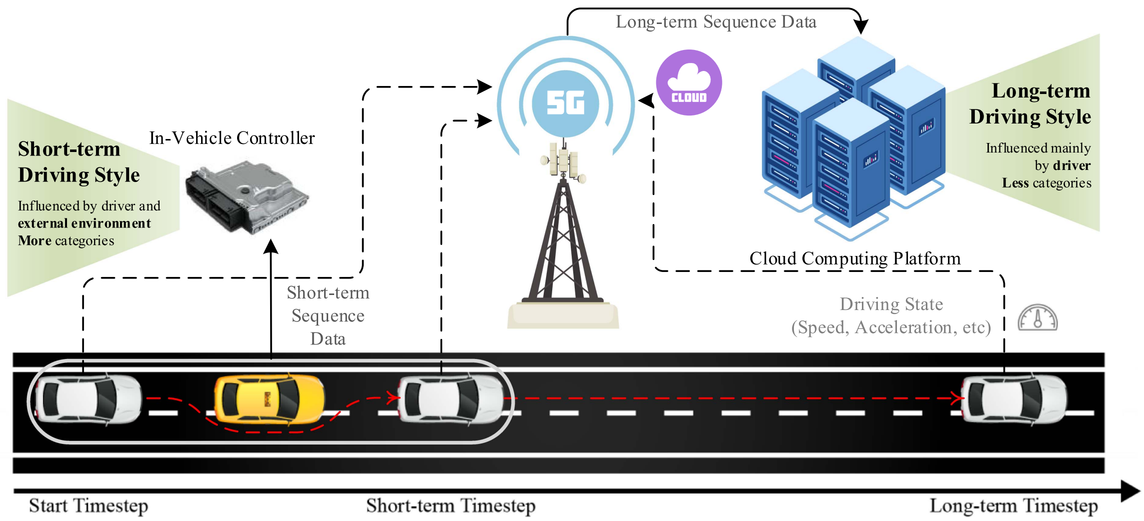

Fig. 1. Differences in definition between short-term and long-term driving styles.

their application. The contributions are fourfold: 1) providing the commons and differences between short- and long-term driving style recognition methods; 2) more comprehensively summarizing existing driving style recognition algorithms and analyzing whether existing algorithms are suitable for short-term or long-term driving style recognition; 3) summarizing existing evaluation metrics to provide the possibility of performance comparison between algorithms; and 4) discussing the shortcomings of existing algorithms and their relevant outlooks.

The remainder of the article is organized as follows. Section II introduces the fundamentals of driving styles, including the definition, influencing factors, and labels. Section III describes data acquisition methods, processing approaches, and inputs for driving style recognition algorithms. Section IV discusses different driving style recognition algorithms and their applicability for long-term and short-term driving styles. Section V shows the metrics for performance evaluation. Section VI describes the applications of driving style recognition in future works.

II. Influencing Factors and Classification of Driving Styles

A. Definition

In summary, the driving style is a generalization of a driver's driving behavior and habits [21], [22], [23], which is influenced by the driver's habits, personality [21], [24], and external factors such as the traffic flow, type of road, and time of day when driving [21], [25], [26]. Given the numerous factors, the definition of driving style is currently inconclusive. Thus, we discuss the driving styles from long-term and short-term views with separate definitions, as shown in Fig. 1.

- Short-term driving style refers to a driver's behavioural characteristics in a driving scenario, and it reflects the driver's different tendency to make choices in different driving scenarios. It usually changes when the current task or scenario changes. It is obtained by analyzing short-term driving data, such as the trajectory of the vehicle driving in a lane-change scenario. The recognized short-term driving style is only valid for the corresponding driving scenario. It is influenced by the driver's habits, personality, emotions, and the current short-term traffic conditions. Accordingly, it is unstable and prone to change. A driver may perform different short-term driving styles at different times. For example, when going to work in a traffic jam, a normal driver may resort to more aggressive behavior than usual to be on time.
- Long-term driving style refers to a driver's behavioral characteristics over a long period of time, rather than in a specific driving scenario. It is obtained by analyzing long-term driving data, such as total lane-change numbers on a route. It is influenced by drivers' habits, personalities and the proficiency of their driving skills. Long-term driving style is stable and may change slowly as driving skills become proficient. For example, the way a bus driver operates a bus on a route is usually consistent, and the passenger experience of riding a bus driven by the same driver is correspondingly consistent, in terms of the average acceleration and deceleration and the average number of lane changes over the route. Furthermore, passengers' perceptions of riding the same route with different bus drivers may vary, due to the different long-term driving styles of different drivers.

B. Influencing Factors

The abovementioned definitions suggest that the factors influencing driving styles can be divided into two groups: driver-related and external environment-related.

- Driver-related factors include two categories: long-term and short-term factors. Drivers' proficiency, habits, and personalities impact their long-term and short-term driving styles [24]. Drivers' driving moods, states, lengths of continuous driving and the task of current driving are susceptible to change as they drive and will only impact their short-term driving styles.

- The factors from the external environment perspective mainly include the type of road currently being driven on, the traffic conditions, the driving behaviors of surrounding drivers, and the weather. The influence of such a factor on a driver exists only for a relatively small period. As defined above, it mainly impacts short-term driving styles and minimally affects long-term driving styles.

C. Driving Style Labels

For the purpose of application, the number of driving style labels should be different for short-term and long-term driving styles. Short-term driving style recognition is mainly used for driver intention prediction and driving behavior analysis. Usually, drivers' intentions and driving behaviors are diverse, and the corresponding driving style should have multiple labels to analyze them accurately. For example, researchers [26] analyzed short-term driving styles by using multiple labels for accurate analysis, such as drowsy, distracted, drunk, eco-friendly, or aggressive labels. Long-term driving style recognition is mainly used for risk assessment, driver habit simulation, and driving skill evaluation, which usually require two or three driving style labels. For instance, researchers [27] recognized bus drivers' long-term driving styles with normal and aggressive styles.

III. Data Acquisition Methods, Preprocessing Approaches and Inputs

Accurate driving style recognition performance requires high-quality and sufficient data. We outline three perspectives as follows: data acquisition, data preprocessing, and model inputs. The different performance requirements of long-term and short-term recognition algorithms are combined to analyze how data should be selected. Fig. 2 shows the different stages from the following three perspectives.

A. Data Acquisition

Data form the basis for achieving driving style recognition. On the basis of the data source, data acquisition methods are divided into two categories: driver data and driving data.

1) Driver Data Acquisition: Driver data can be obtained from questionnaires about drivers or their physiological signals.

Questionnaire analysis about driver: The question set in the Multidimensional Driving Style Inventory (MDSI) consists of driver characteristics (e.g., gender, age, driving experience, etc.) and driving behavior habits (e.g., errors, violations, and mistakes that occur in driving behaviors) [28], [29]. The driving habit questionnaire is somewhat justified [30], which is a basis for the subjective classification of driving styles and the influence analysis of different psychological and physiological factors on driving styles [31].

Drivers' physiological signals: The physiological state of a driver is considered with devices such as cameras, electrocardiogram instruments, and electroencephalogram (EEG) instruments to capture physiological signals, such as drivers' expressions, heart rates, and brain waves [32], [33], [34].

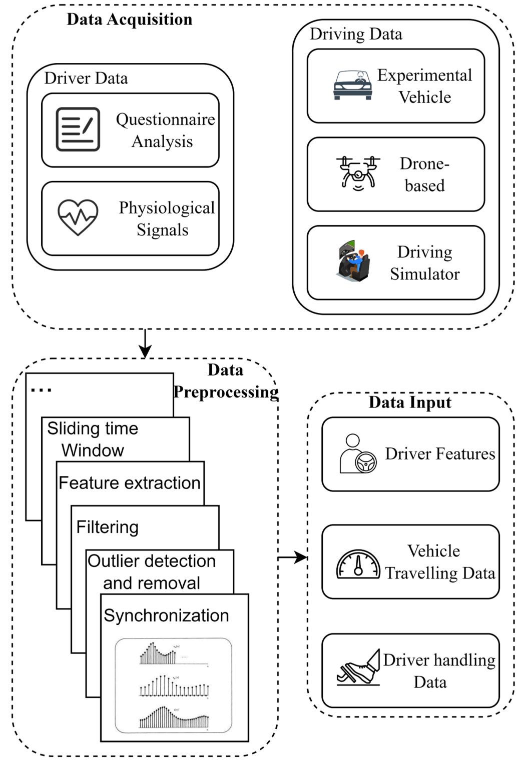

Fig. 2. Summary of each stage of data acquisition, preprocessing, and input.

2) Driving Data Acquisition: Driving data can be obtained from experimental vehicles, drones, and driving simulators.

Experimental vehicle: The experimental vehicle driving data are usually obtained from on-board diagnostics and controller area networks [35], [36], [37], both of which can easily collect driving data and driver handling data. However, the accuracy of the acquired data is difficult to guarantee. More advanced sensors (e.g., accelerometers, global positioning systems, radar, cameras, and inertial measurement units) [38], [39], [40], [41] are gradually being equipped in cars and can collect more driving data at a high cost. Furthermore, smartphones have been used as driving data collection devices [42], [43].

Drone-based: Drone-based data are obtained by extracting vehicle trajectories from bird's eye view videos. The extracted trajectories and vehicle interactions are more comprehensive than those collected from experimental data [44]. Thus, inter-vehicle distance, an important feature in driving style recognition, is easily preserved.

Driving simulators: Acquiring experimental vehicle and drone-based data requires significant funds and manpower [45]. For safety reasons, these data cover a few corner cases. Driving simulators can acquire driving data more safely, especially in extreme situations. This setup requires building specific driving scenarios in driving simulators according to the needs of research.

B. Data Preprocessing

Due to the potential inaccuracy, the high-dimensionality and mismatched formats of raw data, we could not feed the raw data from different sensors to algorithms directly. This study presents five commonly used data preprocessing methods for driving style recognition: synchronization, outlier detection and removal, filtering, feature extraction, and the sliding time window technique.

Synchronization: The sampling frequencies of different sensors often vary. The different sampling frequencies usually need to be synchronized, especially for driving style recognition models with time-based inputs. The method can be divided into two types, upsampling and downsampling. The choice of upsampling and downsampling is usually based on factors such as the volatility of the raw data and data volume. When the amount of data is small, up-sampling to the highest sampling frequency is usually used for synchronization to retain data information and maintain data volume. For this purpose, Saleh et al. [46] used up-sampling to synchronize the driving data collected by smartphone-embeded sensors. However, due to the volatility of row data, Ma et al. [47] downsampled the driving data.

Outlier detection and removal: Outliers are data that depart from the majority of sample points due to external disturbances, sensor faults, etc. The accuracy of the recognition results will be impacted by the outliers; thus, they must be detected and removed at the data preprocessing stage. Statistical methods such as the interquartile range (IQR) and Pauta criterion are often used for outlier detection and removal. Ma et al. [47] employed the Pauta criterion to detect and remove outliers from driving data.

Filtering: A filter is a data processing technique that removes the noise from the data collected by sensors, allowing the data to be suitable for analysis. Typically, the noise recorded by the sensor is high-frequency noise that can be removed with a low-pass filter [48]. Butterworth filters are often used for data preprocessing. Guyonvarch et al. [49] applied a Butterworth low-pass filter to preprocess the acceleration and angular speed signals acquired by inertial measuring units. Savitzky-Golay filters are also often used for driving data preprocessing [50].

Feature extraction: Usually, the acquired raw data are complex and coupling. Feature extraction can reduce the dimension of the raw data and is a common data preprocessing method in driving style recognition. It includes principal component analysis (PCA) [29], the histogram method [19], and the Fourier transform [51]. PCA is used to identify patterns in data and represent them in a way that highlights similarities and differences in data. Once these patterns are found, the data can be compressed by reducing the dimensions [52]. Constantinescu et al. [53] proposed two alternative algorithms based on hierarchical cluster analysis and PCA. PCA was used to investigate the correlation between variables and transform the original dataset into a smaller dataset while retaining useful information.

Sliding time window: The sliding time window technique aims to segment signals into fixed lengths. This technique is widely used in driving style recognition. It can increase the size of the dataset by overlapping segments [27], [54]. Therefore, the accuracy of recognition can be improved using a larger dataset. Khodairy et al. [54] segmented driving data under a specific driving style by using the sliding time window technique.

C. Data Input Types

Data inputs can be broadly classified into driver features, vehicle traveling data, and driver handling data. Driver features include the frequency of certain driving behaviors, EEG signals, heart rate, etc. Driver features consist of two parts of data (questionnaire analysis and drivers' physiological signals), as mentioned in Section III-A. In contrast to the other two types of inputs, these data from drivers can be used to recognize drivers' driving styles without providing driving scenarios [33]. Vehicle traveling data (vehicle status such as speed and acceleration) [27] reflect vehicle dynamics. Given the contribution of vehicle dynamics to superior classification performance [54], vehicle traveling data are widely used in driving style recognition. Driver handling data (e.g., brake pedal and accelerator pedal displacement and steering wheel angular velocity) [55] record how the driver operates the vehicle, which can intuitively reflect a driver's driving behavior and in turn reflect the driver's driving style. Many other types of data are applicable for driving style recognition input. For example, more than 62 features were used to recognize driving styles in the literature [56]. However, constrained by computing power and limitations of onboard sensors, appropriate data inputs must be selected while considering the specific use case of driving style recognition.

D. Existing Datasets

Many existing datasets are available for driving style recognition. With the help of publicly available datasets, we can save considerable time and effort when conducting driving style research. Driving style application scenarios that apply to different datasets are discussed on basis of the characteristics of these datasets.

1) NGSIM I80: The NGSIM dataset was collected by the U.S. Federal Highway Administration (FHWA) in 2005 [57]. Montanino et al. [48] addressed the measurement errors in the dataset and reconstructed the NGSIM I80 dataset. The dataset collected 45 minutes of trajectory data (drone-based data) on a segment of Interstate 80 located in Emeryville, California. These data belong to vehicle traveling data. The dataset is widely used in driving style recognition tasks, especially in car-following situations. However, the dataset is unlabeled with the driving style of each driver; thus, it does not apply to supervised learning. The duration of each car following behavior is short, which might be unsuitable for long-term driving style recognition.

2) HCRL: HCRL is a public dataset with a total driving time of approximately 23 hours [35]. To collect the data, ten drivers conducted round trips of approximately 46 km between Korea University and Sangam World Cup Stadium twice. The data are collected from the experimental vehicle. This dataset has more data than NGSIM, but it is still unlabeled and unsuitable for supervised learning.

3) UAH-Driveset: UAH-DriveSet is a public dataset created for driving style recognition studies published by Alcala University [58]. The data were collected by a mobile phone app called DriveSafe, which obtained data from smartphone sensors. These data belong to the data gathered from experimental data. The dataset collected data from 6 drivers who drove on two

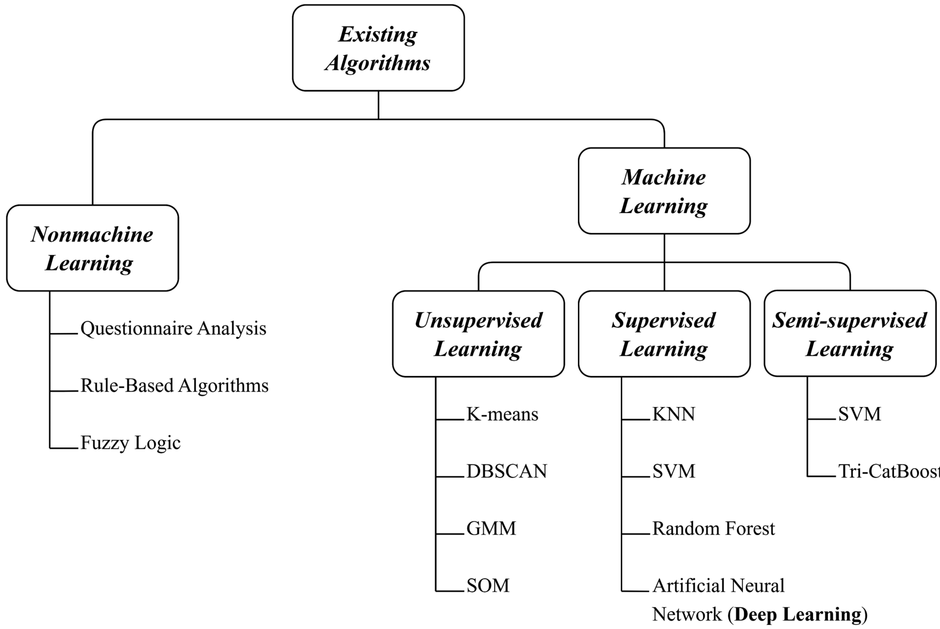

Fig. 3. Brief summary of existing driving style recognition algorithms.

types of roads (motorways and secondary roads). On each type of road, the drivers simulated three different driving styles (normal, aggressive, and drowsy), which resulted in more than 500 minutes of naturalistic driving data. The dataset is labeled, which gives it a significant advantage over unlabeled datasets such as the NGSIM and HCRL datasets. However, the dataset contains only over 500 minutes of driving data, which may seem small when a deep learning approach is used for long-term driving style recognition.

4) Others: In addition to the abovementioned datasets, many other datasets can be used for driving style recognition [26]. The Honda Research Institute Driving Dataset (HDD) contains up to 104 hours of real human driving data [59]. The data were collected using an instrumented vehicle equipped with many sensors. The dataset has a large amount of data and contains many data features. A multimodal dataset was provided by another research [60]. The dataset includes data for 68 drivers and includes many data features. The dataset also has a large data volume and contains physiological features. HCIlab makes their dataset publicly available [61]. The dataset contains approximately 300 minutes of driving data, GPS, brightness, acceleration, physiological information, and video rating data. However, the dataset has a small amount of data. Many other publicly accessible drone-based datasets can be used for driving style recognition, such as the Highway Drone Dataset (highD) [62] and the Exits and Entries Drone Dataset (exiD) [63]. However, none of the datasets mentioned above provide the driver's driving style and are unsuitable for supervised learning.

IV. Driving Style Recognition Algorithms

This section introduces the existing algorithms for driving style recognition and compares the applicability of each algorithm for long-term and short-term driving style recognition to help researchers better design long-term and short-term driving style recognition algorithms. Fig. 3 summarizes the existing driving style recognition algorithms. TABLE I indicates the different algorithms available for driving style recognition.

A. Nonmachine Learning Algorithms

For nonmachine-learning algorithms, artificially prescribed rules (or thresholds) are used to classify driving styles. They mainly include questionnaire analysis, rule-based algorithms, and fuzzy logic[1]. These algorithms are often relatively simple, have strong interpretability, and require minimal computing power but demand high expertise from algorithm designers.

- Questionnaire Analyses
  Self-reports of certain aspects of driver behavior can be used as surrogates for observational measures [90]. Thus, a questionnaire's results can reflect drivers' driving styles to some extent. Lshibashi et al. [30], used PCA to compile a questionnaire for recognizing drivers' driving styles in low-speed following scenarios and tested the validity of the questionnaire by performing correlation analysis with behavioral indices. Wang et al. used the MDSI, the "Big Five" inventory, the driver behavior questionnaire, and several questions about socio demographic information to classify drivers into four driving styles [24]. However, questionnaires are strongly influenced by respondents' subjectivity. Eboli et al. [64] showed that self-defined driving styles might be unreliable and biased. Thus, it is necessary to recognize driving styles based on objective data.
- Rule-Based Algorithms

[1]Whether fuzzy logic belongs to a machine learning algorithm is controversial. Following the study [5], fuzzy logic is classified as a nonmachine learning algorithm in this review.

TABLE I
EXISTING ALGORITHMS FOR DRIVING STYLE RECOGNITION

Class	*Algorithm*	*Recommendation for Short-term or Long-term*	*Reference*
Nonmachine Learning	Questionnaire Analysis	Long-term	[24], [30], [64]
	Rule-Based Algorithm	Long-term	[65], [66], [67]
	Fuzzy Logic	Long-term	[68], [69], [70]
Unsupervised Learning	K-means	- [1]	[36], [71], [72]
	DBSCAN	-	[73]
	DP-means	-	[74]
	GMM	Short-term	[75], [76]
	SOM	-	[77], [78]
Supervised Learning	KNN	Long-term	[27], [79]
	SVM	Long-term	[80], [81]
	Random Forest	Long-term	[40], [82]
Deep Learning	LSTM	Long-term	[46], [54]
	TCN	Short-term	[83], [84]
	CNN	Long-term	[85], [86], [87]
Semi-supervised Learning	SVM	Long-term	[88]
	Tri-CatBoost	Long-term	[89]

[1] Hyphen denotes the suitability of algorithm for both short-term and long-term driving style recognition, and it is difficult to compare which is more suitable.

Rule-based or threshold-based algorithms are the simplest class of algorithms for driving style recognition based on objective data [5]. By using the collected data, with the expertise of the algorithm designers, thresholds are set to recognize drivers' driving styles.

Murphev et al. [65] scored drivers based on the number of aggressive maneuvers observed during driving, and a driver's final score was calculated as a percentage, with a score below 50% judged as a calm driving style and a score higher than 100% judged as an aggressive driving style. Meanwhile, Rath et al. [67], classified driving styles via the lateral jerk signal.

One of the simplest driving style recognition algorithms is an algorithm based on one parameter. However, as only one parameter is used, the selected parameter determines the quality of the driving style recognition results. The choice of the parameter requires a high level of expertise on the part of the designer. Moreover, as only one parameter is considered, the recognition accuracy and robustness are low, and the application scenarios of such an algorithm are relatively narrow.

- Fuzzy Logic

  Given that the accuracy and robustness of driving style recognition algorithms based on one parameter are limited, driving styles can be recognized on the basis of multiple parameters. Although large sets of variables produce unnecessarily complex rules, fuzzy logic can alleviate this problem. Fuzzy logic is also based on predefined thresholds but can include more parameters while maintaining its advantages of simplicity, ease of understanding, and low computational effort [91].

  Dörr et al. [68], built a real-time recognition algorithm based on fuzzy logic. The authors used many data features, such as speed, acceleration, time-interval vehicle spacing, and road type, to recognize driving styles. This algorithm was validated in a simulated environment involving urban and rural roads without traffic disturbances, achieving a 68% correct classification rate and a 2% incorrect classification rate. Castignani et al. [69], not only used in-vehicle signals as fuzzy logic inputs but also considered different driving events and external factors, such as weather and time of day. Finally, they reported a model accuracy of up to 90%.

  One literature [70] attempted to improve the accuracy of a fuzzy logic based driving style recognition model with more inputs, but the experimental results showed that fuzzy logic was less effective than the other two algorithms (time series, Ar2p[2]) because it required the definition of a large rule base to cover all possible situations.

Nonmachine-learning algorithms are relatively simple, easy to implement, and highly interpretable. However, the level of expertise of the algorithm designer can significantly impact the algorithm's recognition accuracy. Traffic conditions vary worldwide, and nonmachine-learning algorithms must be redesigned for different local conditions, giving them narrow application scopes. The number of parameters that rule-based algorithms can handle is limited. However, the accuracy and robustness of algorithms can be further improved by utilizing a large amount of data and input variables to cover all possible situations, as shown in a previous work [70]. With the development of machine learning, its ability to handle large amounts of data, self-learning ability, and low dependence on the professional knowledge of designers has led to increasing interest in the application of machine learning for driving style recognition.

For the sake of accuracy and robustness, nonmachine-learning algorithms require long-term data for recognition and may be unsuitable for short-term driving style recognition.

[2] Algoritmo Recursivo de Reconocimiento de Patrones, for its acronym in Spanish

B. Machine Learning Algorithms

1) Unsupervised Learning: Unsupervised learning requires less driving style recognition knowledge than nonmachine-learning algorithms. It also does not require labeled data, and unlabeled data are much easier to obtain. Clustering algorithms are commonly used classes of unsupervised learning algorithms that cluster data by statistical analysis.

- K-means
  The K-means clustering algorithm is commonly used in driving style recognition. It divides the given data into k clusters such that the intercluster distance is as large as possible and the intracluster distance is as small as possible [92]. Van Ly et al. [36] modeled driving events from driving data, which were then fed into the K-means algorithm for driving style recognition. The number of clusters in the model is two, and the authors reported approximately 60% accuracy. Other features extracted from driving data are also used as inputs to the K-means algorithm, such as temporal driving volatilities [71]. Some studies feed driving data directly for driving style recognition without further feature extraction. de Zepeda et al. [72] fed driving data directly into the K-means algorithm to recognize short- and long-term driving styles and explored the switches from short- to long-term driving styles.
- DBSCAN
  The K-means algorithm requires the user to specify the number of clusters in advance. The obtained clustering results are sensitive to the selection of the initial cluster centers and easily fall into local optima. In contrast, the density-based spatial clustering of applications with noise (DBSCAN) algorithm is a density-based clustering algorithm that does not require the number of clusters to be specified, and the initial cluster centers have less impact on the clustering results. It can better identify and process noisy data and outliers than other approaches [73]. In a study [93], the DBSCAN algorithm was used to recognize driving styles by determining the sensitivity of the model parameters by using a genetic algorithm and reached 95% accuracy when the input data duration was longer than 25 s.
- DP-means
  The traditional DBSCAN algorithm requires a relatively large number of parameters to be set in advance, and the results are sensitive to the set thresholds, while the DP-means algorithm is more robust to thresholds. As the DP-means method depends on the order of the data, the order of driving data is crucial when performing driving style recognition. A study [74] emphasized it when applying DP-means for driving style recognition.
- GMM
  The Gaussian mixture model (GMM) is an expectation maximization (EM) algorithm. In contrast to the above-mentioned clustering algorithms, it employs soft clustering, a data point may be contained in different clusters with different probabilities. Shakib et al. [75] holds that sudden changes in driving style can damage system stability, as each data point can only be associated with one driving style in the case of hard clustering, which leads to difficulty in monitoring abnormal driving behavior, i.e, short-term abnormal driving style. Thus, he used a GMM-based clustering algorithm to recognize short-term driving styles.
- SOM
  A self-organizing map (SOM) is an artificial neural network (ANN) that contains an input layer, and a computational layer [94]. A study [77] indicated that SOMs are effective clustering algorithms and that the workload required for parameter adjustment is small. However, if few neurons are contained in the computational layer of an SOM, its recognition accuracy will be low. In the study, the authors combined an SOM with the K-means algorithm to recognize driving styles. They first used the SOM to obtain preliminary clustering results and then used K-means to cluster the preliminary results to recognize three driving styles. SOMs also have the advantage of being highly interpretable. Taking advantage of this fact, Lakshminarayanan et al. [78] used an SOM model to recognize the driving styles of bus drivers and interpreted the recognition results, which helped to improve their subsequent study.

The features used in clustering algorithms are usually statistical or frequency domain features, and the time dimension is usually compressed. Clustering algorithms generally group data according to their features. Thus, the classification results are generally insensitive to the duration of the input data, and the computational effort is roughly the same. Thus, clustering algorithms, especially hard clustering algorithms, are appropriate for both long-term and short-term driving style recognition. However, owing to the advantages of soft clustering algorithms such as GMM in detecting changes in driving style, we recommend them for short-term driving style recognition, which are more likely to change.

The output results of unsupervised learning are easy to interpret. The given data do not need to be labeled, thus this strategy requires minimal expertise from the algorithm designer. However, for many unsupervised learning algorithms, some parameters need to be set manually in advance, and the choice of these parameters greatly affects the quality of the driving style recognition results. The classification performance of unsupervised learning is worse than that of supervised learning. Classifying data on the boundary between different driving styles is particularly difficult.

2) Supervised Learning: Supervised learning requires algorithm designers to master the basic knowledge of driving style recognition to artificially add driving style labels to the relevant data, but the recognition accuracy is high. Commonly used supervised learning algorithms include k-nearest neighbors (KNN), support vector machines (SVMs), random forests (RFs), and ANNs.

- KNN
  KNN is one of the simplest supervised learning algorithms. The data categories are determined according to the K most similar samples [95].
  Utilizing this algorithm, Vaitkus et al. [27] extracted five features from acceleration data and achieved a 100% classification success rate. However, the same route, season,

and similar traffic circumstances were used to generate the training and test data. Liu et al. [79] used in-vehicle signals and physiological signals as inputs of a KNN model for driving style recognition.

The KNN algorithm stores all the input training data and has high memory requirements. Given the limited storage space of the in-vehicle controller, it may be somewhat unsuitable for short-term driving style recognition based on the in-vehicle controller.

- SVM

An SVM [96] tries to find an optimal hyperplane that separates the training data perfectly into their classes. Zhang et al. [80] developed a window-based SVM model to classify drivers with average accuracies of 75.83%, 85.83%, and 86.67% on three different vehicles. The number of aggressive driving styles in driving style recognition is always relatively small compared with normal driving styles. However, an SVM does not work well when classifying unbalanced datasets. A study [81] applied Random-SMOTE to balance the number of positive and negative samples and then used a cost-sensitive SVM to set different penalty factors for the positive and negative samples, thus improving the model's ability to recognize dangerous driving behaviors (i.e., dangerous short-term driving style).

The traditional SVM algorithm can only be used to solve binary classification problems. The number of required classifications for short-term driving style recognition is large, as shown in Section II-C. Thus, more SVMs will be utilized in the algorithm to recognize more driving styles, which will cause the model to be more complex and require higher demands on the in-vehicle controller's computing power. SVMs may be unsuitable for short-term driving style recognition based on the in-vehicle controller.

- RFs

RFs [36] are sets of decision trees that vote together in a classification task. RFs are known to be effective in preventing overfitting.

A research [40] applied the RF algorithm to recognize aggressive and safe driving styles by using data collected from a 3-axis accelerometer (G-sensor) on a light vehicle and finally obtained a high classification accuracy of 95.5%, which was attributed to the RF algorithm not being easily overfitted. Several classification algorithms, including discriminant analysis, decision trees, KNN, SVM, and RF, were used to recognize driving styles, and their performance was compared in a study [82]. The RF algorithm with Bayesian parameter optimization obtained the highest accuracy for reasons such as overfitting difficulty and automatic feature selection.

RFs can be used to solve multiclassification problems, but many decision trees must be used to prevent overfitting and improve classification accuracy, resulting in slow calculation speeds. However, short-term driving style recognition based on the in-vehicle controller requires a fast recognition speed with not much computing power, which may lead to unsuitable for RFs.

- ANNs

ANNs are nonlinear statistical data modeling tools often used to model complex relationships between inputs and outputs or explore data patterns [97]. During naturalistic driving trips, the data acquired from sensors are always time series data. Thus, the driving style recognition problem can be formulated as a time series classification problem [46]. Time series classification problems are frequently solved using long short-term memory (LSTM) networks, which are recurrent neural network versions that significantly alleviate the vanishing gradient problem by using the gate structure [98]. Khodairy et al. [54] used an optimized Stacked-LSTM model to recognize driving styles and achieved an F1 score exceeding 99%, which demonstrated the excellent performance of LSTM. Similarly, Saleh et al. [46], applied Stacked-LSTM to recognize driving styles based on the UAH-DriveSet dataset, and achieved an F1 score of 91%, which was much higher than the scores of a multilayer perceptron (MLP) and a decision-tree. However, LSTM networks require considerable memory and computing time costs, especially in cases involving long input sequences [99]. Thus, they may be unsuitable for short-term driving style recognition based on in-vehicle hardware, which has high requirements for real-time recognition with small storage spaces and low computing power.

In a temporal convolutional network (TCN), filters are shared across a layer; thus, its memory requirement is much lower than that of LSTM. The computational efficiency of the TCN is also higher than that of LSTM due to computational parallelism. A driving style recognition algorithm based on a TCN and soft thresholding, called S-TCN, was proposed in a previous research [83]. The authors indicated that the S-TCN outperformed the current state-of-the-art (SOTA) driving behavior (i.e, short-term driving style) recognition methods, such as LSTM-FCN and ResNet, with low memory requirements and high computational efficiency. Owing to its great recognition capacity and low memory and computing power requirements, we recommend it for short-term driving style recognition.

Convolutional neural networks (CNNs) have been widely used in image classification and proven to perform well. It has also been successfully applied in some studies to the recognition of driving styles. As CNNs are usually employed to process images rather than time series data, Li et al. [85] mapped natural driving sequential data into two-dimensional pictures, called driving operation pictures (DOPs), which allowed a CNN to be applied to driving style recognition. A similar approach was also used by Shahverdy et al. [87]. Three ANN algorithms, a CNN, an LSTM network, and a trained LSTM network, were applied to recognize driving styles in Li's study and the CNN performed best with an accuracy of 98.5%, also outperforming the traditional SVM approach. However, CNNs are prone to overfitting, especially when input data are small. Bejani et al. [86] applied a CNN to recognize driving styles and used two adaptive regularization methods, called adaptive weight decay and adaptive dropout, to avoid overfitting; they finally obtained a high recognition accuracy of 95%. Although CNN computation is less than LSTM [83], it is still quite large; therefore it may be unsuitable for short-term driving style recognition based on in-vehicle controllers.

Other types of ANNs have also been used for driving style recognition. Schlegel et al. [100] proposed a driving style recognition method combining high-dimensional vector data representation with high-dimensional computing (HDC) and a simple feedforward neural network, which not only achieved similar or slightly better classification results than those of LSTM but also significantly reduced the required training time and yielded improved data efficiency. With the development of ANNs, especially deep learning, they tend to perform well in driving style recognition and are one of the future directions.

Although the classification performance of supervised learning is strong, data labeling is inevitable, which requires high expertise from the algorithm designer, and labeling a large amount of data consumes considerable time and effort. To alleviate this problem, Van et al. [57] explored the combination of K-means and an SVM. The unsupervised K-means algorithm was used to explore the correlations of input data and label them, while the SVM was used to perform driving style recognition based on the K-means labeled data.

3) Semi-Supervised Learning: Semi-supervised learning combines a small amount of labeled data with a large amount of unlabeled data during training, which can save considerable time and effort by avoiding much data labeling. Wang et al. [88] proposed a semi-supervised learning model by first using K-means cluster analysis to select several data clusters for manual labeling, then using a quasi-Newton algorithm to assign optimal labels to the data, and finally classifying the driving styles into aggressive and regular groups via an SVM. For the same purpose. Liu et al. [89], proposed a driving style recognition method based on Tri-CatBoost and conducted extensive experiments on UAH-DriveSet. The authors reported macroscopic accuracy values higher than many unsupervised learning and supervised learning algorithms, such as K-means, a gradient-boosting decision tree (GBDT), an RF, decision trees, and an MLP. The applicability of semi-supervised learning algorithms to long- and short-term driving styles is mostly determined by their learning model. For example, in Wang's work, the learning model is SVM.

V. Algorithm Evaluation Metrics

Different algorithms have different performance characteristics due to differences among their calculation principles; thus, it is necessary to develop and select reasonable performance metrics to evaluate and compare the performance of different algorithms. For comparing algorithms of the same type, there are specific metrics. For example, for clustering algorithms, the silhouette coefficient can be used for evaluation [101]. For different kinds of algorithms, some common metrics exist to allow comparison of different algorithms. Common metrics can also be used to select algorithms according to different needs (long-term or short-term driving style recognition). Since many evaluation metrics exist among the same type of algorithms, only common evaluation metrics are presented in this section to guide different algorithms for long- and short-term driving style recognition applications.

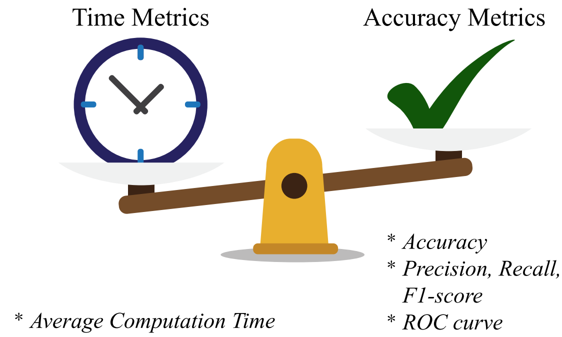

Fig. 4. Common evaluation metrics for driving style recognition algorithms.

A. Existing Common Metrics

The existing common evaluation metrics are mainly divided into accuracy metrics and time metrics. Accuracy metrics, which describe an algorithm's recognition accuracy, mainly include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve (AUC). However, this metric is only suitable for cases with available ground truth. Time metrics, which describe an algorithm's recognition speed, mainly refer to the average computation time of the recognition algorithm. Other existing performance metrics are also available, such as interpretability, which describes the difficulty of understanding models' internal logic and inner workings. Fig. 4 shows the evaluation metrics utilized for driving style recognition algorithms.

1) Accuracy Metrics:

- Accuracy
  Accuracy is one of the simplest performance metrics for measuring accuracy and is the performance metric selected in most studies if the correct sample labels are provided. Xue et al. [102] selected accuracy as a performance metric to compare an SVM, an RF, KNN, and an MLP. However, when the positive class dominates, high accuracy can be easily achieved as long as we predict the sample to be positive [103]. When recognizing driving styles, the sample size of drivers with a normal driving style is usually larger than the sample size of drivers with other driving styles. Thus, the constructed model may still perform poorly in driving style recognition even when obtaining a high accuracy value.
- Precision, recall, and F1-score
  Precision and recall are better metrics for unbalanced datasets. Precision is the proportion of actually correct positive identifications, and recall is the proportion of correctly identified actual positives. They are often in tension, and only when both metrics are high will the model perform well. A more concise and practical approach is to combine

precision and recall into a single metric, the F1-score, as defined in (1):

$$F1 - score = \frac{Precision \times Recall}{Precision + Recall}. \tag{1}$$

If both the precision and recall values are high, then the model will obtain a high F1 score. For the unbalanced dataset, Silva et al. [104] selected the F1-score instead of accuracy as the performance metric to compare ANN, SVM and RF algorithms.

- ROC curve
  ROC curves are based on ROC graphs, in which the false-positive rate is plotted on the X-axis, and the true-positive rate is plotted on the Y-axis. In contrast to the abovementioned performance metrics, ROC curves are insensitive to class distribution changes. The AUC is defined as the area under the ROC curve. If the performance of the classifier is superior, then the AUC is close to 1. If the classifier performance is poor, then the ROC curve is close to a straight line, and the AUC is close to 0.5. Zepf et al. [105] produced the ROC curve of their driving style recognition model to evaluate its performance and calculated a corresponding AUC of 88.7%.

2) Time Metrics: The performance of a recognition model can be evaluated by considering not only accuracy metrics but also time metrics, i.e., the computational complexity of the model, especially when recognizing short-term driving styles with a high update frequency. The common time metric is the average computation time. It can be divided into two metrics: the average training time per epoch and the average prediction time per sample. They are mainly related to the complexity of the algorithm and the input data. Zhao et al. [83], used the average computation time to evaluate the complexity of different deep-learning based methods for driving style recognition.

3) Others: Some other metrics can also be used to evaluate the performance of an algorithm, such as interpretability. Many algorithms, especially ANNs, have good driving style recognition performance are black-box models. The internal logic and inner workings of these models are difficult to explain. A research [106] indicated that a single metric, such as accuracy, provides incomplete descriptions of most real-world tasks. Thus, model interpretability must be evaluated, even if the model has a good recognition performance. Doshi-Velez et al. [106] proposed three main levels of experiments to evaluate interpretability. However, given the lack of uniformity in the definition of interpretability, it is still difficult to evaluate model interpretability [107].

B. Summary and Shortcomings of Existing Studies

Short-term driving style recognition, mainly used for driver intention prediction and driving behavior monitoring, must recognize driving styles in the shortest possible time with relatively low-dimensional inputs. Thus, the time metric is important for evaluating how well a short-term driving style algorithm performs. The main application for long-term driving style recognition is to optimize the design of advanced automotive systems and autonomous driving systems. Thus, such an algorithm needs to have a high recognition accuracy. The accuracy metric is important for evaluating how well a long-term driving style algorithm performs. Given the high demand for driving safety, driving style recognition algorithms should be interpretable.

However, the performance metrics in the existing studies often vary from one test environment to another, even under the same algorithm. Vaitkus et al. [27], used accelerometer data and selected seven features to recognize driving styles with a KNN model, and the accuracy of the test set reached 100%. However, in another study [108] that compared the performance of several recognition algorithms, including the KNN algorithm, the recognition accuracy of the KNN model was only 68%. This finding represents a large difference, and the main reason for this result is the lack of consistency in the algorithmic input data and the selection of the test sets. 1. Different algorithms use different features from driving data, which can greatly impact the algorithms' performance. 2. The selected datasets are inconsistent and differ in amount and type. 3. Even though the same dataset is used in some studies to compare different algorithms, the performance comparison results of different studies are not the same due to the differences in test set selection, resulting in a lack of objectivity in the performance comparison results of different algorithms. These scenarios lead to a lack of objective comparisons among different existing driving style recognition algorithms.

VI. Future Applications

New connectivity and personalization features will be increasingly implemented with software for intelligent vehicles in the future. The driver's experience of the vehicle will be shaped from the original hardware to the software. The software cannot be separated from driving style recognition to meet the driver's individual needs. Driving style recognition will have increasingly important applications in emerging autonomous vehicle fields.

The future applications of driving style recognition can be divided into personalized service recommendations and autonomous driving.

A. Personalized Service Recommendation

Personalized service recommendation makes the human–machine interface (HMI) recommend some applications according to the driver's preferences [109], [110]. For example, when the driver prefers sport, the HMI recommends some appropriate parameters of the powertrain [111]. The driver chooses whether to accept the recommendation by using the software, not by means of a hardware button. The service recommendation's reasonableness mainly depends on understanding the driver's driving behaviors and driving styles. Customized and personalized services influence people's trust and acceptance of autonomous vehicles [112]. Zhu et al. [113] recognized driving style by analyzing driver braking behavior and designed a personalized basic booster control strategy based on driving style to effectively enhance the personalization of the braking system, resulting in higher pedal response and user acceptance.

B. Personalized Autonomous Driving

Personalized or customized autonomous driving refers to autonomous vehicles adapting their driving preferences according to different drivers and driving scenarios. For example, the driving actions of the same autonomous vehicle in the same scenario are different between young and old drivers and between aggressive and conservative drivers [114]. A self-learning optimal cruise controller that can automatically adapt to individual car-following styles is developed for the individual driver in [115]. Human-like driving is also important in personalized autonomous driving. Reinforcement learning (RL) and inverse reinforcement learning (IRL) are widely used in the field of human-like driving [116]. Liu et al. [117] used an IRL algorithm to train an automated lane change system, and the well-trained system automatically adjusted the system parameters for different driving styles. In another research [118], the authors designed different reward functions for reinforcement learning for different driving styles, allowing autonomous vehicles to adapt to human-driving habits.

VII. Conclusion

Driving style recognition is active in many automotive scenarios, such as driver intention prediction and autopilot systems. This review comprehensively explores driving style recognition from an application and implementation perspective. Specifically, it divides the available driving style recognition methods into short-term and long-term recognition approaches from these two perspectives. This research is the first to divide driving style recognition into long-term and short-term perspectives. First, short-term and long-term driving styles are defined, and their characteristics, such as influencing factors and labels, are given. Then, the utilized data inputs and preprocessing approaches are briefly described. In addition, the existing driving style recognition algorithms are reviewed, and their applicability for short-term and long-term recognition is compared. Furthermore, this review investigates the existing evaluation metrics for these algorithms from multiple perspectives, such as accuracy, time, and interpretability metrics. Finally, the applications of driving style recognition in future vehicles, especially autonomous vehicles, are described. Thus, this study can help researchers quickly implement short-term or long-term driving style recognition methods depending on their application purposes and application platforms.

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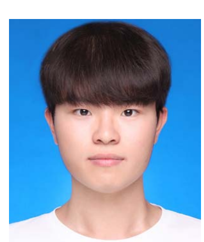

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