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Gu, Yi, Chen, Zhiyu, Wang, Lu, Shen, Jinsong, Bashir, Ali Kashif and Wang, Wei (2024) Driving Behavior Safety Assessment in Edge Computing Using Multitask Discriminative TS Fuzzy Model. IEEE Transactions on Consumer Electronics. ISSN 0098-3063

**DOI:** https://doi.org/10.1109/tce.2024.3518591

**Publisher:** Institute of Electrical and Electronics Engineers (IEEE)

**Version:** Accepted Version

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# Driving Behavior Safety Assessment in Edge Computing Using Multitask Discriminative TS Fuzzy Model

Yi Gu, Zhiyu Chen, Lu Wang, Jinsong Shen, Ali Kashif Bashir, Wei Wang

***Abstract*—Driving behavior safety analysis in edge computing involves the real-time collection and processing of vehicle driving data. Fuzzy models have advantages in analyzing driving behavior due to their excellent ability to handle uncertain information. This study develops a multitask discriminative Takagi-Sugeno fuzzy model (MD-TS-FM) for driving behavior safety assessment. To comprehensively analyze the correlation and differences in multitask driving behaviors, the designed consequent part consists of two parts: task-shared part reflects the shared intrinsic structure information that are consistent across different driving tasks, and task-specific part reflects distinct characteristics and variations specific to each task, allowing the model to address the unique aspects of different driving behaviors. Accordingly, the task-shared consequent part is characterized by low-rank property, which mines global structural information within the fuzzy space; whereas the task-specific consequent part exhibits sparsity, which removes non-discriminative and irrelevant information. This sparsity ensures that the model focuses on the most critical features for each specific task. Furthermore, a discriminative diversity term is introduced to enhance the diversity between tasks, which explores the consistent information of task-shared consequents while reducing the overlap of task-specific consequents. Experimental results indicate that the MD-TS-FM model can be effectively applied to driving behavior safety assessment.**

This work was supported in part by the Natural Science Foundation of Jiangsu Province under Grant BK20210449; in part by the Fundamental Research Funds for the Central Universities under Grant JUSRP122035. (Corresponding author: Yi Gu.)

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***Index Terms*—driving behavior safety assessment, fuzzy model, edge computing, multitask learning**

## I. INTRODUCTION

With the robust development and utilization of perception and communication technologies, edge computing in Internet of Vehicles (IoV) has become a crucial component of Intelligent Transportation Systems (ITS)[1,2]. The relationships among data collection, transmission, and storage of driving behaviors in edge computing are illustrated in Fig. 1. Edge computing in IoV conducts wireless communications and information exchanges based on vehicle communication standard protocols and defined categories of information. This supports cooperative vehicle decision-making control, collaborative intelligent traffic management and information services, as well as internet and travel services. Particularly, the use of sensors built into or attached to vehicles allows for real-time acquisition of critical vehicle data, including travel time, speed, and engine revolutions per minute (RPM), etc.

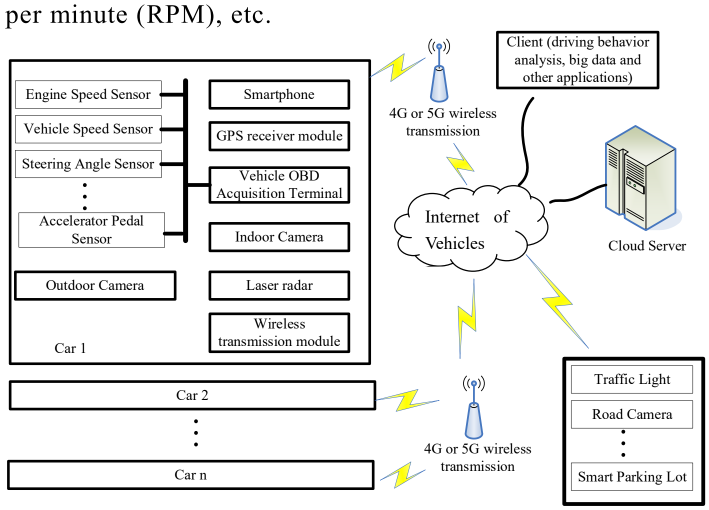



Fig. 1 Collection, transmission, storage, and analysis of driving behavior data in edge computing-IoV

By analyzing these data, one can deeply study drivers' behaviors, thereby providing strong support for identifying and predicting potentially dangerous driving actions [3]. For example, Feng et al. [4] designed an intelligent driving diagnosis assistance system that utilized vehicle sensors to collect data on driving behavior. The system input this data into a binary regression model, which classified dangerous driving behaviors into three risk categories: high, medium, and low. Karrouchi et al. [5] proposed a system that evaluated driving state and style based on both driving operations and the driver's facial reactions. This system collected data from the vehicle's Controller Area Network (CAN) to determine whether the driving behavior was smooth or aggressive. By analyzing the driver's facial expressions, this system can provide a more comprehensive assessment of the driver's state and style, leading to personalized feedback and improvements in driving habits. Ding et al. [6] analyzed traffic conflicts on highway sections using clustering techniques based on vehicle trajectory data. They used improved surrogate safety measures to calculate the probability and severity of vehicle collisions in edge computing.

One of the challenges in driving risk assessment lies in dealing with the uncertainty of different driving behaviors [7]. Drivers exhibit a wide range of driving styles, which are shaped by various factors such as personality, experience, culture, and attitudes towards risk. Fuzzy inference is indeed a powerful tool for handling uncertainty and complexity in driving behavior analysis [8]. It simulates human thinking and can effectively handle intelligent driving problems, demonstrating flexibility and adaptability. For example, Alam et al. [9] used the fuzzy Analytic Hierarchy Process (AHP) to evaluate dangerous driving behaviors. The AHP is essentially a structured technique for dealing with complex decisions that involve multiple criteria. By applying fuzzy logic to the AHP, the researchers were able to analyze and rank various alternatives, taking into account the subjective differences among drivers and the inherent uncertainty in assessing driving behavior. Ronquillo-Cana et al. [10] proposed a system for assessing dangerous driving behavior by integrating data from objective sensors, such as acceleration, steering, position, and speed, with subjective driver questionnaires. This system employed a rule-based fuzzy inference method to integrate the results of objective and subjective classification systems, providing a more comprehensive assessment of driving behavior. Eftekhari et al. [11] designed a neuro-fuzzy system to evaluate driver behavior. This system addressed the uncertainty challenges in judging driving actions by classifying them based on similarity to predefined fuzzy patterns. However, these fuzzy models are essentially modeled using traditional single-task learning strategy. Single-task fuzzy models train a separate model for each task, often neglecting the relationships among multiple tasks and potentially losing some information that exists between data or model parameters. Particularly when data is scarce, single-task fuzzy models may struggle to gather sufficient data distribution information.

In driving behavior safety assessment, accurate analysis of driver behavior data is crucial. Multitask learning offers a promising solution to this challenge by leveraging the connections between tasks to enhance overall performance [12]. Therefore, we propose a multitask discriminative Takagi-Sugeno fuzzy model (MD-TS-FM). The proposed model designs multitask fuzzy rules and focuses on learning multitask consequent parameters to address the limitations of single-task fuzzy models. The MD-TS-FM model encapsulates consensus information across diverse tasks within the rule consequents, referred to as task-shared consequent part, thereby facilitating the exploration of intertask correlations. Additionally, each task's rule consequent includes specific information for that task, referred to as task-specific consequent part, which reflects distinct characteristics to each task. Accordingly, the MD-TS-FM model endeavors to reveal the inherent link among multi-tasks within the consequent part. It postulates that the task-shared consequent part embodies a low-rank structure, whereas the task-specific consequent part exhibits sparsity characteristics. Simultaneously, a discriminative diversity term is introduced to promote consistency in task-shared consequent part and minimizes redundancy in task-specific consequent part. The experimental results on real-world datasets confirm the effectiveness of the MD-TS-FM model in learning better consequent parameters and fully exploring the relationships between tasks. Empirical validation substantiates the superior performance of the proposed model compared to other fuzzy models. MD-TS-FM can better detect and respond to different driving behaviors.

The contribution of this study is as follows:

(1) The study introduces a novel multitask learning model that integrates TS-fuzzy model from multiple tasks for joint learning. The proposed model can significantly enhance the accuracy and reliability of driving behavior safety assessments by capturing the interdependencies and unique characteristics of different driving scenarios.

(2) Within the TS fuzzy model framework, the study proposes a new method for multitask fuzzy consequent learning. The consequent part of the fuzzy rules is ingeniously divided into two components. Task-shared consequent part captures common patterns and knowledge that are applicable across all tasks. Task-specific consequent part focuses on unique characteristics specific to each individual task. Moreover, the low-rank and sparsity constraints are introduced. The low-rank constraint encourages the task-shared part to capture generalizable patterns, while the sparsity constraint promotes simplicity and interpretability in the task-specific part.

(3) Discriminative diversity term is introduced to minimize overlap between task-specific consequents across different tasks. Thus, the model can better differentiate between various driving tasks, enhancing its performance and ability to capture task-specific details. Concurrently, leveraging disparities in task-specific representations enhances the performance of multitask learning.

In Section II, an overview of fuzzy rule model is introduced. The multitask discriminative TS fuzzy model is described in Section III. The comparison experiments and results are presented in Section IV. Finally, Section IV concludes the study.

## II. RELATED WORK

Fuzzy rule model is an approach to implementing fuzzy reasoning using natural language, which utilizes IF-THEN rules to describe the complex nonlinear relationships between inputs and outputs in the framework of fuzzy set theory. The Takagi-Sugeno(TS) fuzzy model is characterized by its strong approximation ability, simple structure and straightforward implementation mechanism

[13, 14]. The fundamental concept of TS model involves partitioning the global nonlinear fuzzy model into several fuzzy subspaces, each representing a specific aspect or feature of the system. Within these subspaces, simple linear relationship models are established using linear combinations of the fuzzy rules.

Given the input variable $\mathbf{z}=[z_1,z_2,...,z_d]\in\mathbf{R}^d$, $A_j^i$ is the fuzzy subset of the $j$th multivariate fuzzy set in the $i$th rule. $A_j^i$ achieves the partitioning of the data space. The structure of the $i$th rule is as follows:

IF $z_1$ *is* $A_1^i \wedge z_2$ *is* $A_2^i \wedge ... \wedge z_d$ *is* $A_d^i$,

$$\text{Then}\begin{cases} y_1^i(\mathbf{z}) = p_{1,0}^i + p_{1,1}^i z_1 + \cdots + p_{1,d}^i z_d \\ y_2^i(\mathbf{z}) = p_{2,0}^i + p_{2,1}^i z_1 + \cdots + p_{2,d}^i z_d \\ \vdots \\ y_k^i(\mathbf{z}) = p_{k,0}^i + p_{k,0}^i z_1 + \cdots + p_{k,d}^i z_d \end{cases} \tag{1}$$

THEN part of the fuzzy rule indicates a local linear model established in the $i$th $(1\le i\le c)$ fuzzy subspace. $\mathbf{p}_j^i=[p_{j,0}^i,...,p_{j,d}^i]\in\mathbf{R}^{d+1}$ and $y_j^i(\mathbf{z})\in\mathbf{R}^{d+1}$ represent the consequent parameters and rule output, respectively. $c$ and $k$ are the number of fuzzy rules and dimensions of output, respectively.

For a given input $\mathbf{z}$, the final output of the TS fuzzy model is the weighted sum of the outputs from local linear models, where the weights are the degrees of membership of $\mathbf{z}$ in each fuzzy set,

$$f(\mathbf{z}) = \frac{\sum_{i=1}^{c} u_i(\mathbf{z}) y^i(\mathbf{z})}{\sum_{i=1}^{c} u_i(\mathbf{z})} = \sum_{i=1}^{c} \bar{u}_i(\mathbf{z}) y^i(\mathbf{z}), \tag{2}$$

where $u_i(\mathbf{z})$ and $\bar{u}_i(\mathbf{z})$ are fuzzy membership and normalized fuzzy membership respectively,

$$u^i(\mathbf{z}) = \prod_{j=1}^{d} u_{A_j^i}(z_j), \tag{3}$$

$$\bar{u}^i(\mathbf{z}) = u_i(\mathbf{z}) / \sum_{i'=1}^{c} u_{i'}(\mathbf{z}), \tag{4}$$

$$u_{A_j^i}(z_j) = exp(-(z_j - B_j^i)^2/(2\delta_j^i)), \tag{5}$$

where the antecedent parameters $\mathbf{B}^i=[B_1^i,...,B_d^i]$ and $\boldsymbol{\delta}^i=[\delta_1^i,...,\delta_d^i]$ are often computed by fuzzy $C$-means (FCM)-based clustering algorithms. $\mathbf{B}^i$ can be considered as the $i$th clustering center. The element $\delta_j^i$ in $\boldsymbol{\delta}^i$ can be computed as,

$$\delta_j^i = h\sum_{m=1}^{n} \mu_{mj}(z_{mj}^i - B_j^i)^2 / \sum_{m=1}^{n} \mu_{mj}, \tag{6}$$

where $h$ is the scale parameter. $\mu_{nj}$ is the fuzzy membership obtained via clustering algorithms. $n$ is the number of samples.

Denote the matrices as follows,

$$\bar{\mathbf{z}}^i = \bar{u}^i(\mathbf{z})[1,\mathbf{z}^T]^T \in \mathbf{R}^{d+1}, \tag{7}$$

$$\varpi(\mathbf{z}) = [(\bar{\mathbf{z}}^1)^T, (\bar{\mathbf{z}}^2)^T, ..., (\bar{\mathbf{z}}^c)^T]^T \in \mathbf{R}^{c(d+1)}, \tag{8}$$

$$\mathbf{P} = \begin{bmatrix} \mathbf{p}_1^1 & \cdots & \mathbf{p}_k^1 \\ \vdots & \ddots & \vdots \\ \mathbf{p}_1^c & \cdots & \mathbf{p}_k^c \end{bmatrix} \in \mathbf{R}^{c(d+1)\times k}. \tag{9}$$

The output of TS fuzzy model in Eq. (2) is rewritten as,

$$f(\mathbf{z}) = \mathbf{P}^T \varpi(\mathbf{z}). \tag{10}$$

Given the training dataset $\mathbf{Z}\in\mathbf{R}^{d\times n}$ and its output $\mathbf{F}\in\mathbf{R}^{n\times k}$, the consequent part of the rules is often obtained using the least squares method,

$$\min_{\mathbf{P}} \left\|\mathbf{P}^T\varpi(\mathbf{Z}) - \mathbf{F}\right\|_2^2 + \gamma\left\|\mathbf{P}\right\|_F^2, \tag{11}$$

where $\varpi(\mathbf{Z}) = [\varpi(\mathbf{z}_1),...,\varpi(\mathbf{z}_n)] \in \mathbf{R}^{c(d+1)\times n}$. $\gamma$ is the tradeoff parameter.

## III. Multitask Discriminative TS Fuzzy Model

### A. Rule Construction in MD-TS-FM

The MD-TS-FM fuzzy model aims to address the limitations of traditional fuzzy models by incorporating multitask learning capabilities. This allows the model to handle multiple tasks simultaneously, leveraging shared knowledge between tasks and improving overall performance. Assuming there are $\bar{T}$ tasks with datasets $\mathbf{Z}_t\in\mathbf{R}^{d\times n_t}$ and their label $\mathbf{F}_t\in\mathbf{R}^{n_t\times k}$, where $1\le t\le\bar{T}$. The $i$th fuzzy rule for the $t$th task is,

IF $z_{t1}$ is $A_{t1}^i \wedge z_{t2}$ is $A_{t2}^i \wedge\cdots\wedge z_{td}$ is $A_{td}^i$,

$$\text{Then}\begin{cases} y_1^i(\mathbf{z}_t) = (v_{1,0}^i + q_{1,0}^i) + (v_{1,1}^i + q_{1,1}^i)z_{t1} + \cdots + (v_{1,d}^i + q_{1,d}^i)z_{td} \\ y_2^i(\mathbf{z}_t) = (v_{2,0}^i + q_{2,0}^i) + (v_{2,1}^i + q_{2,1}^i)z_{t1} + \cdots + (v_{2,d}^i + q_{2,d}^i)z_{td} \\ \vdots \\ y_k^i(\mathbf{z}_t) = (v_{k,0}^i + q_{k,0}^i) + (v_{k,1}^i + q_{k,1}^i)z_{t1} + \cdots + (v_{k,d}^i + q_{k,d}^i)z_{td} \end{cases} \tag{12}$$

Define $\mathbf{V} = \begin{bmatrix} \mathbf{v}_1^1 & \cdots & \mathbf{v}_k^1 \\ \vdots & \ddots & \vdots \\ \mathbf{v}_1^c & \cdots & \mathbf{v}_k^c \end{bmatrix} \in \mathbf{R}^{c(d+1)\times k}$ and $\mathbf{Q}_t = \begin{bmatrix} \mathbf{q}_1^1 & \cdots & \mathbf{q}_k^1 \\ \vdots & \ddots & \vdots \\ \mathbf{q}_1^c & \cdots & \mathbf{q}_k^c \end{bmatrix} \in \mathbf{R}^{c(d+1)\times k}$ as the task-shared consequent part and task-specific consequent part for the $t$th task, respectively. $\mathbf{V}$ aims to explore the shared knowledge and captures general relationships that are relevant across different tasks. $\mathbf{Q}_t$ aims to explore the unique characteristics of each individual task that cannot be generalized to other tasks.

Let $\varpi(\mathbf{z}_t) = [(\bar{\mathbf{z}}_t^1)^T, (\bar{\mathbf{z}}_t^2)^T, ..., (\bar{\mathbf{z}}_t^c)^T]^T$, the output for the $t$th task is written as,

$$f_t(\mathbf{z}_t) = (\mathbf{V} + \mathbf{Q}_t)^T \varpi(\mathbf{z}_t). \tag{13}$$

The fuzzy rules used in the MD-TS-FM model can be designed to be applicable across different tasks.

### B. Consequent Learning in MD-TS-FM

In multitask learning, low-rank and sparsity constraints are a popular strategy that improves model performance by encouraging the sharing of information across related tasks and promoting model generalization [15]. Specifically, MD-TS-FM adopts this by imposing low-rank constraint on the task-shared consequent part; at the same time, MD-TS-FM imposes $\ell_{2,1}$ -norm sparse constraint on the task-specific consequent part. Therefore, we obtain the low-rank and sparse constraint term,

$$\min_{\mathbf{V},\mathbf{Q}} \alpha \sum_{t}^{\bar{T}} \|\mathbf{Q}_t\|_{2,1} + \beta Rank(\mathbf{V}), \tag{14}$$

where $\alpha$ and $\beta$ are the tradeoff parameters. The choice of the $\ell_{2,1}$ -norm sparse constraint is motivated by several advantages. Unlike the commonly used $\ell_1$-norm sparse, which induces element-wise sparsity, the $\ell_{2,1}$-norm promotes group sparsity. This is particularly useful when task-specific consequent part is naturally grouped [16]. Such sparsity can greatly simplify the model and improve its interpretability. Compared to $\ell_1$ -norm constraint, which can result in non-differentiable points in the optimization landscape, $\ell_{2,1}$ -norm constraint is differentiable everywhere and often easier to optimize. This can lead to more stable and efficient optimization solution. In addition, $\ell_{2,1}$ -norm is less sensitive to outliers than $\ell_1$ -norm because it does not emphasize large values as much. This makes it more robust to data noise and outliers in real-world scenarios.

Existing fuzzy models often neglect the interrelationships among distinct consequent parameters. However, considering the heterogeneity inherent in related tasks, it is reasonable to assume that the task-specific components of different tasks should vary significantly. Each task-specific consequent part should exhibit minimal similarity to others, with discernible differences across various tasks and a weak connection to the task-shared consequent part. To address this, we introduce the discriminative diversity term,

$$\min_{\mathbf{V},\mathbf{Q}} \sum_{t}^{\bar{T}} (\lambda Tr(\mathbf{Q}_t^T \mathbf{V}) + \gamma \sum_{t \neq r} Tr(\mathbf{Q}_t^T \mathbf{Q}_r)), \tag{15}$$

where $\lambda$ and $\gamma$ are the tradeoff parameters.

In MD-TS-FM, the task-shared consequent part is isolated from distinct tasks, reflecting discriminative rules across various tasks. Intuitively, amplifying the difference between $\mathbf{V}$ and $\mathbf{Q}_t$, as well as the divergence among different tasks, can enhance the discriminative ability of rule consequents. Therefore, the objective function of consequent leaning in MD-TS-FM is,

$$\begin{aligned}\min_{\mathbf{V},\mathbf{Q}} \sum_{t}^{\bar{T}} (\|\varpi(\mathbf{Z}_t)^T(\mathbf{V}+\mathbf{Q}_t) - \mathbf{F}_t\|_F^2 + \alpha \|\mathbf{Q}_t\|_{2,1} + \lambda Tr(\mathbf{Q}_t^T \mathbf{V}) + \gamma \sum_{t \neq r} Tr(\mathbf{Q}_t^T \mathbf{Q}_r)) \\ + \beta Rank(\mathbf{V}).\end{aligned} \tag{16}$$

### C. Parameter Optimization

The nuclear-norm effectively approximates the low-rank constraint [17]. Given its convex nature, the nuclear-norm can be readily addressed through matrix factorization technique. Therefore, we incorporate the nuclear-norm constraint $\|\mathbf{V}\|_*$ on $\mathbf{V}$ into the objective function,

$$\begin{aligned}\min_{\mathbf{V},\mathbf{Q}} \sum_{t}^{\bar{T}} (\|\varpi(\mathbf{Z}_t)^T(\mathbf{V}+\mathbf{Q}_t) - \mathbf{F}_t\|_F^2 + \alpha \|\mathbf{Q}_t\|_{2,1} + \lambda Tr(\mathbf{Q}_t^T \mathbf{V}) + \gamma \sum_{t \neq r} Tr(\mathbf{Q}_t^T \mathbf{Q}_r)) \\ + \beta \|\mathbf{V}\|_*,\end{aligned} \tag{17}$$

By introducing the auxiliary variables $\mathbf{\Theta}$, Eq.(17) can be written as,

$$\begin{aligned}\min_{\mathbf{V},\mathbf{Q},\mathbf{\Theta}} \sum_{t}^{\bar{T}} (\|\varpi(\mathbf{Z}_t)^T(\mathbf{V}+\mathbf{Q}_t) - \mathbf{F}_t\|_F^2 + \alpha \|\mathbf{Q}_t\|_{2,1} + \lambda Tr(\mathbf{Q}_t^T \mathbf{V}) + \gamma \sum_{t \neq r} Tr(\mathbf{Q}_t^T \mathbf{Q}_r)) \\ + \beta \|\mathbf{\Theta}\|_*, \\ s.t. \mathbf{V} = \mathbf{\Theta}\end{aligned} \tag{18}$$

We solve Eq. (18) through the Augmented Lagrange Multiplier (ALM) method. Eq. (18) can be rewritten as,

$$\begin{aligned}\min_{\mathbf{V},\mathbf{Q},\mathbf{\Theta},\mathbf{H}} \sum_{t}^{\bar{T}} (\|\varpi(\mathbf{Z}_t)^T(\mathbf{V}+\mathbf{Q}_t) - \mathbf{F}_t\|_F^2 + \alpha \|\mathbf{Q}_t\|_{2,1} + \lambda Tr(\mathbf{Q}_t^T \mathbf{V}) + \gamma \sum_{t \neq r} Tr(\mathbf{Q}_t^T \mathbf{Q}_r)) \\ + \beta \|\mathbf{\Theta}\|_* + \frac{\mu}{2} \left\| \mathbf{V} - \mathbf{\Theta} + \frac{\mathbf{H}}{\mu} \right\|_F^2,\end{aligned} \tag{19}$$

where $\mathbf{H}$ is the Lagrange multiplier. $\mu > 0$ is the penalty parameter.

1) Update $\mathbf{V}$. Fixing $\mathbf{Q}$, $\mathbf{H}$, and $\mathbf{\Theta}$, the objective function of $\mathbf{V}$ is,

$$\min_{\mathbf{V}} \sum_{t}^{\bar{T}} (\|\varpi(\mathbf{Z}_t)^T(\mathbf{V}+\mathbf{Q}_t) - \mathbf{F}_t\|_F^2 + \lambda Tr(\mathbf{Q}_t^T \mathbf{V})) + \frac{\mu}{2} \left\| \mathbf{V} - \mathbf{\Theta} + \frac{\mathbf{H}}{\mu} \right\|_F^2. \tag{20}$$

Taking the first derivative of $\mathbf{V}$, we obtain,

$$\mathbf{V} = (2\varpi(\mathbf{Z}_t)\varpi(\mathbf{Z}_t)^T + \mu \mathbf{I})^{-1}(2\varpi(\mathbf{Z}_t)(\varpi(\mathbf{Z}_t)^T \mathbf{Q}_t - \mathbf{F}_t) - \lambda \mathbf{Q}_t + \mu \mathbf{\Theta} - \mathbf{H}) \tag{21}$$

2) Update $\mathbf{Q}_t$. Fixing $\mathbf{V}$, $\mathbf{H}$, and $\mathbf{\Theta}$, the objective function of $\mathbf{Q}_t$ is,

$$\min_{\mathbf{Q}} \sum_{t}^{\bar{T}} (\|\varpi(\mathbf{Z}_t)^T(\mathbf{V}+\mathbf{Q}_t) - \mathbf{F}_t\|_F^2 + \alpha \|\mathbf{Q}_t\|_{2,1} + \lambda Tr(\mathbf{Q}_t^T \mathbf{V})) + \gamma \sum_{t \neq r} Tr(\mathbf{Q}_t^T \mathbf{Q}_r) \tag{22}$$

According to the definition of $\ell_{2,1}$ -norm, $\|\mathbf{Q}_t\|_{2,1} = Tr((\mathbf{Q}_t)^T \mathbf{D}_t \mathbf{Q}_t)$, where $\mathbf{D}_t$ is the diagonal matrix with the diagonal elements $(d_t)_{i,i} = 1/(2\|(\mathbf{Q}_t)_i\|_2)$. Eq.(22) can be rewritten as,

$$\min_{\mathbf{Q}} \sum_{t}^{\bar{T}} (\|\varpi(\mathbf{Z}_t)^T(\mathbf{V}+\mathbf{Q}_t) - \mathbf{F}_t\|_F^2 + \alpha Tr((\mathbf{Q}_t)^T \mathbf{D}_t \mathbf{Q}_t) + \lambda Tr(\mathbf{Q}_t^T \mathbf{V})) + \gamma \sum_{t \neq r} Tr(\mathbf{Q}_t^T \mathbf{Q}_r) \tag{23}$$

Taking the first derivative of $\mathbf{Q}_t$, we obtain,

$$\mathbf{Q}_t = (2\varpi(\mathbf{Z}_t)\varpi(\mathbf{Z}_t)^T + 2\alpha \mathbf{D}_t)^{-1}(2\varpi(\mathbf{Z}_t)(\varpi(\mathbf{Z}_t)^T \mathbf{V} - \mathbf{F}_t) - \lambda \mathbf{V} - 2\gamma \sum_{t \neq r} Tr(\mathbf{Q}_r)) \tag{24}$$

3) Update $\mathbf{\Theta}$. Fixing **V**, **H**, and $\mathbf{Q}_t$, the objective function of $\mathbf{\Theta}$ is,

$$\min_{\mathbf{\Theta}} \beta \|\mathbf{\Theta}\|_* + \frac{\mu}{2}\left\|\mathbf{V}-\mathbf{\Theta}+\frac{\mathbf{H}}{\mu}\right\|_F^2 . \tag{25}$$

According to the Singular Value Thresholding algorithm [18], we obtain,

$$\mathbf{\Theta} = \vartheta_{\frac{\beta}{\mu}}(\mathbf{V}+\mathbf{H}/\mu) . \tag{26}$$

where $\vartheta_\varepsilon(x) = \mathrm{sgn}(x)\times\max(|x|-\varepsilon,0)$ is the soft threshold operator, $\mathrm{sgn}(x)$ is the sign function.

4) Update **H**. Fixing **V**, $\mathbf{\Theta}$, and $\mathbf{Q}_t$, the objective function of **H** is,

$$\min_{\mathbf{H}} \left\|\mathbf{V}-\mathbf{\Theta}+\frac{\mathbf{H}}{\mu}\right\|_F^2 . \tag{27}$$

Taking the first derivative of **H**, we obtain,

$$\mathbf{H} = \mathbf{H} + \mu(\mathbf{V}-\mathbf{\Theta}), \tag{28}$$

$$\mu = \min(\rho\mu, \mu_{\max}), \tag{29}$$

where $\rho$ is the number of iterations.

The algorithm description of the MD-TS-FM model is shown in Algorithm 1.

Algorithm 1. The MD-TS-FM model

Input: Multitask data $\{\mathbf{Z}_t, \mathbf{F}_t\}_{t=1}^{\bar{T}}$ for $\bar{T}$ tasks, number of fuzzy rules, tradeoff parameters $\alpha$, $\beta$, $\lambda$, and $\gamma$, scalar parameter $h$;

Output: Fuzzy rules and output function.

Step 1: Obtain antecedent parameter **B** using the fuzzy clustering algorithm;
Step 2: Obtain antecedent parameter $\boldsymbol{\delta}$ by Eq.(6);
Step 3: Obtain $\varpi(\mathbf{Z}_t) = [\varpi(\bar{\mathbf{z}}_{t,1}), \varpi(\bar{\mathbf{z}}_{t,2}), ..., \varpi(\bar{\mathbf{z}}_{t,n_t})]$ by Eqs.(7-8);
Repeat
  Step 4: Update **V** by Eq.(21);
  Step 5: Update $\mathbf{Q}_t$ by Eq.(24);
  Step 6: Update $\mathbf{\Theta}$ by Eq.(26);
  Step 7: Update **H** by Eqs.(28)-(29);
Until Objective function Eq.(19) converges or reaches the maximum number of iterations;
Step 8: Generate fuzzy rules for each task by Eq.(12);
Step 9: Obtain output function for each task by Eq.(10).

# IV. Experiments

## A. Datasets and Experiment Setup

To evaluate the performance of the proposed MD-TS-FM model, experimental validation is conducted using the DDD20 dataset [19] and the D2CAV dataset [20]. These datasets include driving behavior data and GPS data from multiple road segments of various durations. The recorded data include accelerator pedal status, brake pedal status, steering wheel rotation angle, gearbox gear, longitude, latitude, engine RPM, etc. To better recognize driving behaviors, we introduce a set of features derived from a period of driving data, including: accelerator pedal presses, maximum speed, brake pedal presses, average speed, standard deviation of speed, maximum acceleration, maximum deceleration, maximum lateral acceleration, average acceleration, average deceleration, average yaw rate during lane changes, number of lane changes, average pitch rate during turns, number of turns, number of times exceeding speed limit. The acceleration of sample *n* on road segment *i* is $a_{n,i}$, $a_{n,i} = (v_t - v_{t-w})/w$, where $v_t$ is the instantaneous velocity of sample *n* at time *t*, and *w* represents the time interval. For identifying lane change maneuvers, a directional angle deviation exceeding 10° along a road segment, followed by a return within ±5°, indicates a lane change. Regarding turning actions, successive directional angles surpassing 90° within a specific time window are considered as turning events.

The experimental duration is set as 40 seconds. Driving behaviors are classified into three distinct types: cautious, aggressive, and fatigued driving. The cautious driving pattern is characterized by consistent speed, minimal acceleration, and moderate steering amplitude. In contrast, aggressive driving is marked by frequent sharp accelerations, forceful braking, and substantial steering. Fatigued driving manifests through erratic vehicle trajectories and frequent lane alterations. The driving scenes include city, campus, freeway, town, and highway—each considered as a separate learning task. Each task comprised 60 samples for a total of 300 samples.

In this study, we compare the MD-TS-FM fuzzy model with several other fuzzy models. These include two single-task TSK fuzzy models—L2-TSK-FS [13] and TSFS-SVR [14], and four multitask TS fuzzy models: MT-TSK-FS [21], mtSparseTSK [22], MW-TSKFS [23], and MT-TSK-FC [24]. Following [21], in multitask fuzzy models, the FCM algorithm is applied to partition all the training data into subsets. Each subset is considered as a rule, which enables different tasks to share antecedent part in the fuzzy rules. The number of fuzzy rules is chosen from the set {3, 4,..., 15}. The tradeoff parameters are selected from the set $\{2^{-6}, 2^{-4}, ..., 2^{6}\}$. The scalar parameter *h* is selected in the gird $\{0.1, 0.2, ..., 1\}$. Finally, it is set as 0.5 empirically. A 5-fold cross-validation is adopted for model training. The experiments are conducted 8 times. In the experiment, accuracy, F-measure, G-means, and recall serve as the evaluation metrics.

## B. Performance Comparison

The recognition results of various TS fuzzy models are presented in Table I. This Table compares the accuracy, F-measure, G-means, and recall indicators of driving behavior. The recognition performance of each fuzzy model varies across tasks, potentially due to the distribution characteristics of the data samples themselves. All multitask fuzzy models outperform single-task fuzzy models, indicating that multitask learning can improve the classification performance. It is also evident that the MD-TS-FM model outperforms single-task models in terms of recognition performance. MD-TS-FM achieves the highest accuracy of 96.72% in identifying driving behavior across five tasks. Specifically, for the city task (Task1), the proposed MD-TS-FM enhances classification accuracy by 6.89% over L2-TSK-FS, and by 7.24%, 5.59% and 6.88% in

F-measure, G-means, and recall respectively. Compared to the second-best model MW-TSKFS, MD-TS-FM achieves improvements of 3.30%, 3.53%, 2.17%, and 2.83% in G-means, F-measure, and recall, respectively. In the highway task (Task5), the baseline model L2-TSK-FS records a classification accuracy of 90.82%, G-means, F-measure, and recall at 91.05%, 90.84%, and 91.03%, respectively. Compared to L2-TSK-FS, our proposed MD-TS-FM model achieves improvement of 6.92%, 5.87%, 7.01%, and 6.16% in classification accuracy, F-measure, G-means, and recall, respectively. Thus, the MD-TS-FM model is more suitable for driving behavior safety assessment than the compared fuzzy models.

The recognition accuracy of various fuzzy models in three types of driving behavior is shown in Table II. Cautious driving behavior has the highest accuracy, while aggressive and fatigue driving have slightly lower accuracy. Consistent with daily experience, cautious driving behavior is characterized by small fluctuations in speed, low frequency of acceleration and deceleration, and smooth changes in steering angle. This suggests that fuzzy models can easily recognize this behavior. Aggressive driving behavior involves drastic speed changes, larger acceleration and deceleration, and significant variations in steering angle. Fatigued driving is marked by large speed fluctuations, frequent steering angle changes, and multiple lane departures. These behaviors are more likely to be confused due to their similarities and the complexity of the driving conditions. In addition, the results in Tables I-II further support the advantages of multitask models over single-task learning models. Especially, the MD-TS-FM model has the highest recognition performance in each category, proving its effectiveness in driving behavior safety assessment. This suggests that it has effectively learned the underlying patterns and characteristics of each behavior. Its ability to monitor drivers' behavior in real time, issue warnings when necessary, and reduce risks associated with disoperation makes it a valuable tool for improving road safety.

Table I The recognition results of various TS fuzzy models

| Index | | L2-TSK-FS | TSFS-SVR | MT-TSK-FS | mtSparseTSK | MW-TSKFS | MT-TSK-FC | MD-TS-FM |
|---|---|---|---|---|---|---|---|---|
| Accuracy | Task1 | 90.71 | 90.52 | 93.52 | 93.36 | 94.30 | 93.38 | **97.60** |
| | Task2 | 89.87 | 91.55 | 92.56 | 94.52 | 93.82 | 93.29 | **96.32** |
| | Task3 | 90.07 | 91.98 | 91.78 | 94.44 | 93.67 | 93.31 | **95.14** |
| | Task4 | 89.34 | 91.95 | 92.35 | 93.33 | 93.48 | 93.07 | **96.80** |
| | Task5 | 90.82 | 90.34 | 93.68 | 93.23 | 94.93 | 94.10 | **97.74** |
| | Average | 90.16 | 91.27 | 92.78 | 93.78 | 94.04 | 93.43 | **96.72** |
| G-means | Task1 | 90.44 | 91.16 | 93.21 | 94.70 | 94.15 | 93.03 | **97.68** |
| | Task2 | 88.63 | 91.07 | 92.45 | 93.66 | 93.91 | 93.16 | **96.60** |
| | Task3 | 89.43 | 91.42 | 91.26 | 93.03 | 93.17 | 91.99 | **95.01** |
| | Task4 | 88.73 | 90.88 | 91.95 | 91.92 | 92.81 | 91.58 | **95.44** |
| | Task5 | 91.05 | 90.76 | 93.65 | 94.68 | 94.74 | 93.76 | **96.92** |
| | Average | 89.66 | 91.06 | 92.50 | 93.60 | 93.76 | 92.70 | **96.29** |
| F-measure | Task1 | 91.19 | 90.86 | 92.66 | 92.89 | 94.61 | 93.52 | **96.78** |
| | Task2 | 90.28 | 92.10 | 92.00 | 94.00 | 93.65 | 93.22 | **95.77** |
| | Task3 | 90.56 | 90.86 | 92.62 | 93.35 | 94.53 | 94.04 | **95.25** |
| | Task4 | 88.94 | 91.15 | 93.94 | 93.53 | 93.25 | 93.08 | **96.58** |
| | Task5 | 90.84 | 90.89 | 93.97 | 94.11 | 94.58 | 93.91 | **97.85** |
| | Average | 90.36 | 91.17 | 93.04 | 93.58 | 94.12 | 93.55 | **96.45** |
| Recall | Task1 | 90.28 | 91.20 | 92.37 | 93.42 | 94.33 | 93.30 | **97.16** |
| | Task2 | 89.41 | 91.50 | 92.02 | 93.97 | 93.22 | 93.24 | **95.85** |
| | Task3 | 90.54 | 91.05 | 91.84 | 93.07 | 94.09 | 92.72 | **95.86** |
| | Task4 | 89.06 | 90.73 | 92.60 | 93.66 | 92.95 | 92.77 | **96.80** |
| | Task5 | 91.03 | 90.81 | 93.05 | 93.65 | 94.37 | 93.04 | **97.19** |
| | Average | 90.06 | 91.06 | 92.38 | 93.56 | 93.79 | 93.01 | **96.57** |

The bold values in Tables I-II means the best experiment results.

Table II The recognition accuracy in three types of driving behavior of various fuzzy models

| | L2-TSK-FS | TSFS-SVR | MT-TSK-FS | mtSparseTSK | MW-TSKFS | MT-TSK-FC | MD-TS-FM |
|---|---|---|---|---|---|---|---|
| Class 1 | 92.38 | 92.80 | 94.52 | 95.57 | 96.18 | 95.31 | **98.58** |
| Class 2 | 89.10 | 90.05 | 91.99 | 92.71 | 92.77 | 92.42 | **95.70** |
| Class 3 | 89.02 | 90.95 | 91.82 | 93.05 | 93.18 | 92.56 | **95.88** |

Table III The antecedent part of each rule for Task1 by MD-TS-FM

| | Feature1 | Feature2 | …… | Feature6 | Feature7 | Feature8 | Feature9 | …… | Feature14 | Feature15 |
|---|---|---|---|---|---|---|---|---|---|---|
| Rule1 | 0.25 | 0.25 | …… | 0.25 | 0.25 | 0.5 | 0.25 | …… | 0.25 | 0 |
| Rule2 | 0.75 | 0.75 | …… | 0.75 | 0.5 | 0.75 | 0.75 | …… | 0.5 | 1 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Rule3 | 1 | 1 | …… | 0.75 | 1 | 0 | 0 | …… | 1 | 1 |
| Rule4 | 0.75 | 0.5 | …… | 0.5 | 0.5 | 0.25 | 0.5 | …… | 0.75 | 0.5 |
| Rule5 | 0 | 0.25 | …… | 0.25 | 0 | 1 | 0 | …… | 0 | 0 |
| …… | …… | …… | …… | …… | …… | …… | …… | …… | …… | …… |
| Rule10 | 0.5 | 0.75 | …… | 0.125 | 0.75 | 0 | 0.75 | …… | 1 | 0.75 |

### C. *Analysis of Fuzzy Rule*

The number of fuzzy rules for all fuzzy models is shown in Fig. 2. The MD-TS-FM model obtains ten rules for each task, equivalent to the MW-TSKFS model. With a small number of rules, the MD-TS-FM model is concise, which is essential in applications like driving behavior safety assessment where rule interpretability is important. The MD-TS-FM model applies low-rank constraint on task-shared consequent part. This constraint encourages cooperation among tasks by identifying common structures in the data that can be shared across tasks. In addition, the MD-TS-FM model applies $\ell_{2,1}$ -norm sparsity constraint on task-specific consequent part. $\ell_{2,1}$ -norm sparsity constraint promotes attention to the most relevant features for each task, reducing overlap and enhancing distinctiveness in the fuzzy space. This sparsity constraint can also help in consequent parameter selection. By applying low-rank and sparsity constraints, the MD-TS-FM model strengthens its classification performance.

To guarantee the semantic precision of rules, we relocate the centers of the membership functions to the nearest grid partition. The procedure for repositioning the centers of membership functions is illustrated in Fig. 3. Here, green circles denote the original centers of membership functions derived from FCM algorithm, red circles represent the fine-tuned centers following relocation, and triangles signify the input variables within the membership functions. The antecedent part of each rule for Task1 by MD-TS-FM is shown in Table III. We can easily descript the membership functions for each fuzzy set in a given linguistic variable, such as very low(0), low(0.25), middle(0.5), high(0.75), very high(1). For example, the linguistic description of the antecedent part of Rule1 shown in Table III can be written as:

*IF Accelerator pedal presses is Low, and Maximum speed is low, and Brake pedal presses is Low, and Average speed is low, and Standard deviation of speed is Very low, and Standard deviation of speed is low, and Maximum acceleration is low, and Maximum deceleration is middle, and Maximum lateral acceleration is low, and Average acceleration is low, Average yaw rate during lane changes is low, and Number of lane changes is Very low, and Average pitch rate during turns is Very low, and Number of turns is low, and Number of times exceeding speed limit is Very low.*

Therefore, the MD-TS-FM model demonstrates adaptability by optimizing its rule parameters to better fit each task, thereby enhancing performance across all tasks. The tuned membership functions allow the model to handle uncertainty and imprecision in the data, increasing its robustness and adaptability to various scenarios. The MD-TS-FM model has a concise model structure while maintaining good performance. This balance is crucial in fuzzy models, as it allows for easier understanding of the model without sacrificing performance. Therefore, the results highlight the potential of MD-TS-FM in advancing driving behavior safety evaluations.

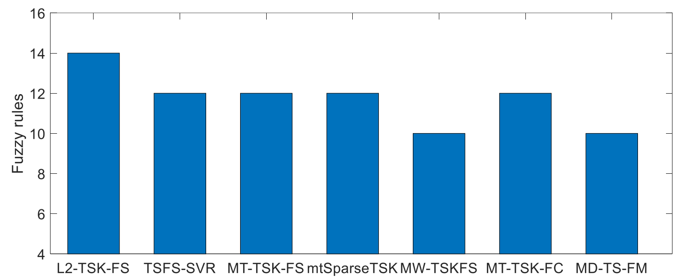



Fig. 2 Fuzzy rules for all fuzzy models

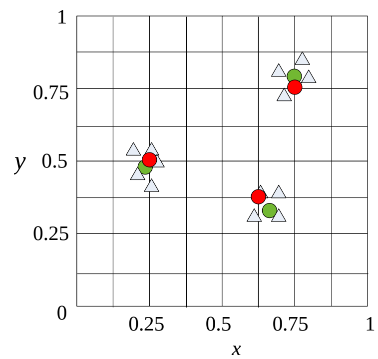



Fig. 3 Example of adjusting centers of membership functions

### D. *Parameter Sensitivity Analysis*

First, we analyze the performance of the MD-TS-FM model from the perspective of the number of fuzzy rules. To achieve the highest accuracy, it is crucial to find an optimal number of fuzzy rules that balances coverage of driving behavior with avoidance of redundancy. Therefore, we determine this optimal number through cross-validation in this study. The experimental result is shown in Fig. 4. The performance of the MD-TS-FM is influenced by the number of fuzzy rules. When the number of fuzzy rules is less than 5, MD-TS-FM has lower accuracy. This occurs because too few fuzzy rules may not provide sufficient information for accurate driver behavior classification. In this case, the model may not be able to capture all the nuances and variations in driving behavior. When the number of fuzzy rules reaches ten, MD-TS-FM obtains the highest accuracy. when the number of fuzzy rules exceeds 13, the accuracy rate of MD-TS-FM decreases a little. An excessive number of rules increases the risk of overlapping, leading to confusion and inaccurate classification. Therefore, MD-TS-FM achieve satisfactory accuracy when the number of fuzzy rules is in the range [10, 12].

Second, we analyze the performance of the MD-TS-FM model from the perspective of the parameter sensitivity and reveals how different parameters affect the model's performance. The tradeoff parameters that need to be optimized include $\alpha$, $\beta$, $\lambda$, and $\gamma$. The experimental results are shown in Fig.5. $\alpha$ adjusts the sparsity term of task-specific consequent part. $\ell_{2,1}$-norm sparsity promotes attention to the most relevant rules for each task, potentially improving model performance. From Fig. 5 (a), we can see that a larger value of $\alpha$ makes the matrix $\mathbf{Q}_t$ sparser, leading to a higher accuracy recognition. This indicates that by focusing on fewer but more impactful task-specific consequent part, our model can achieve better recognition performance. $\beta$ adjusts the low-rank constraint of the task-shared consequent part. The low-rank constraint encourages the model to find commonalities across tasks, which can lead to more efficient representation. From Fig.5(a), we can see that different $\beta$ result in changes in model performance, but the fluctuations are within a small range. This suggests that low-rank constraint can help maintain stability in model performance. $\lambda$ and $\gamma$ are discriminative diversity term parameters. These parameters are tradeoff parameters for the diversity between the task-shared consequent part and the task-specific consequent part. They encourage the model to explore differences between tasks and enhance discriminability. From Fig.5(b), we can see when $\lambda$ and $\gamma$ are greater than 1, MD-TS-FM tends to stabilize and reach a higher recognition performance. This suggests that increasing the difference between the task-shared and task-specific parts, as well as exploring the differences between task-specific part of different tasks, can enhance the model's ability to distinguish between tasks, leading to better performance.

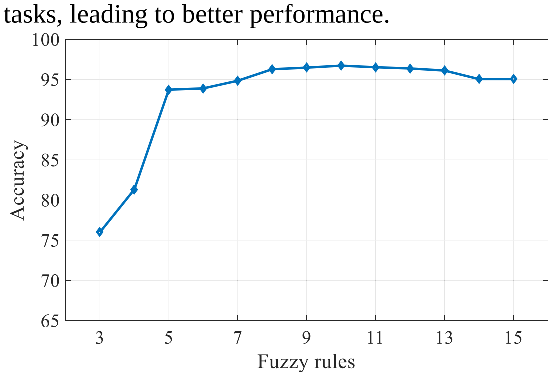
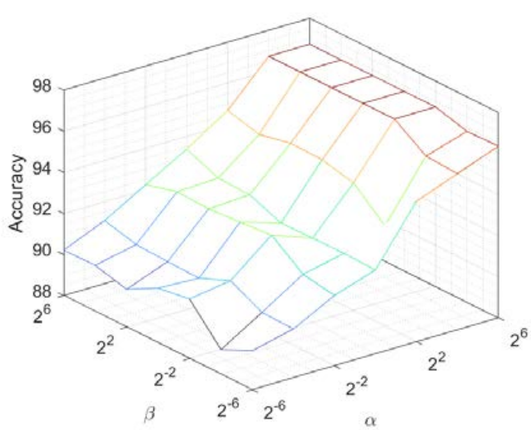
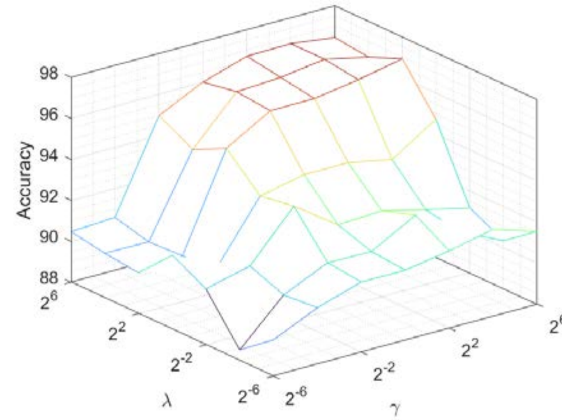



Fig. 4 Analysis of number of fuzzy rules in MD-TS-FM




(a)




(b)

Fig.5 Parameter sensitivity of MD-TS-FM, (a) $\alpha$ and $\beta$, (b) $\lambda$ and $\gamma$

## V. Conclusion

The diversity and complexity of driving behavior among car drivers greatly affect road traffic safety. In recent years, edge computing in IoV technology has emerged as a powerful tool for evaluating and refining these driving behaviors to enhance road safety. This paper proposes a multitask discriminative TS fuzzy model MD-TS-FM. MD-TS-FM leverages the fuzzy model's ability to manage uncertain information, thereby addressing the diversity and complexity in driving behaviors. Additionally, it enhances the model's recognition capabilities in multitask learning scenarios with limited training sets. Specifically, in multitask consequent parameter learning, the MD-TS-FM model utilizes a task-shared consequent part across multiple tasks while maintaining task-specific consequent part. The task-shared consequent part retains the consistency between different tasks, while the task-specific consequent part preserves the diversity across tasks. The experimental results on the DDD20 and D2CAV datasets confirm the effectiveness of the MD-TS-FM model in learning better consequent parameters and fully exploring the relationships between tasks. This model can contribute to the development of advanced driver assistance systems that can better detect and respond to different driving behaviors. However, one identified limitation of our model is its reliance on labeled and completed driving data, which restricts the model's flexibility and adaptability. Thus, our future research could explore dynamic adjustment mechanisms for feature selection to enhance the model's responsiveness to changing data patterns. Additionally, combining the fuzzy model with advanced techniques, such as deep learning, could lead to hybrid models that leverage the high-order feature learning capabilities of deep networks. This integration could improve the model's fitting ability for complex data and potentially yield more accurate identification in diverse driving scenarios. Furthermore, integrating data from various sensors and sources, such as CAN bus data or environmental factors, could provide a more comprehensive understanding of driving behaviors and further enhance the model's performance.

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