Importance Weighted Gaussian Process Regression for Transferable Driver Behaviour Learning in the Lane Change Scenario

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***Abstract*—Due to advantages of handling problems with nonlinearity and uncertainty, Gaussian process regression (GPR) has been widely used in the area of driver behaviour modelling. However, traditional GPR lacks the ability of transferring knowledge from one driver to another, which limits the generalisation ability of GPR, especially when sufficient data for driver behaviour modelling are not available. To solve this limitation, in this paper, a novel GPR model, Importance Weighted Gaussian Process Regression (IWGPR) is proposed. The importance weight (IW) represents the probabilistic density ratio between two drivers and the unconstrained least-squares importance fitting (ULSIF) is applied to calculate IW. Meanwhile, an IW-based model selection (IWMS) method is proposed to help the model select optimal parameters. Using IWGPR, sufficient historical data collected from one driver can be used to model another driver with insufficient data, and thus improve the generalisation ability of GPR. To verify the proposed algorithm, a toy regression problem is used to illustrate the working mechanism of IWGPR. With simulated and naturalistic driving data, three experiments for driver behaviour modelling in the lane change scenario, are designed and carried out. Experimental results indicate that IWGPR performs better than GPR when sufficient data are not provided by the new driver, which proves the generalisation ability of IWGPR. Meanwhile, the comparative study between different transferable driver behaviour learning methods is detailed and analysed.**

***Index Terms*—Transfer Learning, Gaussian Process Regression, Driver Behaviour Learning, the Lane Change Scenario, Importance Weighted Model Selection.**

I. Introduction

Modelling and predicting driver behaviours are crucial to the design of intelligent transportation systems (ITS), advanced driver assistance systems (ADAS) and autonomous driving systems (ADS) [1]–[5]. To precisely model and predict behaviours of drivers, in the recent decade, various machine learning (ML) methods based on statistical learning [6], deep learning [7]–[9] and reinforcement learning [10] have been developed and applied in a number of driving scenarios, such as car following, lane changing, overtaking and many other scenarios [2], [11].

As one of the most popular statistical ML methods, Gaussian process regression (GPR) has gained increasing attention in the area of driver behaviour modelling, because this kind of method is capable of handling problems with high dimensionality, small samples and nonlinearity [12], [13]. Compared with other popular ML approaches, such as artificial neural network (ANN) and support vector machine (SVM), GPR can choose hyper-parameters of model adaptively, evaluate predicted results with the degree of confidence and flexibly infer results of the model with non-parametric methods [12].

However, an important assumption for using GPR is that training and testing datasets should follow the same distribution, which is difficult to conform in real-world applications [14]. Therefore, GPR model trained using driving data collected from one driver may not fit another driver with a different distribution on driving data. For a new driver, a straightforward way to build an effective driver model is to collect sufficient driving data from the new driver and cover scenarios and situations as many as possible. But in practical applications, the collection, pre-processing and labelling of driving data are time-consuming and need high financial support [15], [16]. Under such circumstances, an alternative approach named transfer learning (TL) is proposed in recent years. TL can train an effective model for the new task and scenario without collecting sufficient data [17]. Based on TL and GPR, a novel model for transferable driver behaviour learning, IWGPR, is proposed in this paper to overcome limitations of traditional GPR.

Using the knowledge transferred from other tasks or datasets, TL can speed up the learning process and improve the performance of model in new tasks or datasets even when training data are insufficient [17]. Therefore, TL has earned a great success in fields of deep learning (DL) [18], reinforcement learning [19], natural language processing (NLP) [20] and robot control [21]. In this paper, we pay more attention on the robotics control and intelligent vehicles [10], [22]–[27], in which TL is applied as an effective method to improve the performance of traditional learning-based algorithms.

In the field of intelligent vehicles, a TL method modifying traditional Procrustes analysis algorithm is proposed in [23], [25], [26], which is firstly applied in [22] to learn robot models. In these works, drivers in lane-changing scenarios with different

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driving behaviours can be modelled effectively by using manifold alignment (MA) between two drivers. [24] and [27] propose to model TL between two drivers by adapting marginal and conditional distributions, which separate the process of distribution adaptation and model training. The regression model itself is not combined with TL by formulating regressive functions. Besides the model for drivers using operational data (e.g., steering wheel angle and vehicle longitudinal speed), models for recognizing driving behaviour by images are also developed by combining TL to speed up the learning process. For example, a DL method based on convolutional neural network (CNN) is proposed in [7] and [28] to recognize the drivers' secondary task. A "fine-tune" transferable method is combined with CNN to reduce time consumption in the training process. Based on deep neural network (DNN), Generative Adversarial Networks (GAN) is developed for knowledge transfer in intelligent vehicles [29], [30]. By combining GAN and TL, [30] proposes a "Real-to-Virtual" domain unification method for image-based end to end autonomous driving, which transfers real driving data to virtual domain by unsupervised domain adaptation. [29] proposes an unsupervised framework to automatically and accurately generate driving scenes for the verification of algorithms, which provides a promising approach to measuring the robustness of systems.

Although many works have been done to model driver behaviours, researches based on statistical learning methods mainly focus on generating a new dataset from different drivers for model training process by MA and distributions adaptation, in which the model itself has not been modified. Compared to IWGPR, both methods above lack the ability in describing the problem by density ratio in the objective function and cannot combine data generation into the process of driver behaviour modelling. The objective function and loss function of above two models are independent and uncorrelated with the process of data generation. Few researchers consider applying the density ratio into GPR and formulate a novel object function, which applies the ratio of marginal distribution into statistical ML methods.

The proposed method in this paper is based on the importance weight (IW), which can be combined with kernel-based methods by modifying the kernel function. As an important category of TL, the IW-based TL methods are developed and applied in regression and classification [31]–[33]. These methods can apply the probabilistic density ratio into kernels for knowledge transfer. Although the above related studies have combined TL and GP, limited researches focus on the probabilistic density ratio (IW) or covariate shift adaptation, which represents the relation between source and target drivers. Here drivers with sufficient and insufficient data are named as source and target drivers, respectively. Different from existing researches, this paper proposed a novel importance weighted Gaussian process regression (IWGPR) method based on probabilistic density ratio with the application on driver behaviour learning. Main contributions of this research are as follows:

1) A novel transferable driver behaviour learning method, IWGPR, is proposed by formulating IW into general GPR, which effectively models the new driver with insufficient driving data.

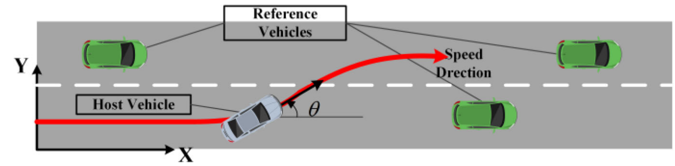


Fig. 1. A general lane change scenario.

2) To verify the proposed algorithm, the toy regression example is selected to present the mechanism of IWGPR. Driving data collected from the simulated environment, highway and urban traffic road are applied to demonstrate the performance of IWGPR in different scenarios.
3) The comparative study between different transferable driver behaviour learning methods is detailed and presented. The proposed method, IWGPR, is developed by estimating the density ratio of marginal distributions. In experiments, compared to previous researches [24], the influence of marginal and conditional distributions adaptation is analysed.

This paper is organised as follows. Section II shows the problem formulation of IWGPR by comparing with general GPR (without transfer) and the detailed methodology for the proposed method is presented. Section III describes the novel importance weighted model selection method for IWGPR and illustrates the architecture for IWGPR by pseudo-code. Four experiments: the toy regression problem and the application in lane change scenarios with simulated, public naturalistic driving data and on road collected driving data, are designed and detailed in Section IV, respectively. Conclusions and future work are presented in Section V.

II. Importance Weighted Gaussian Process Regression

The lane change scenario considered in this paper is shown in Fig. 1. In this scenario, the driver in the host vehicle tries to change to the adjacent lane without hitting reference vehicles. A successful lane change highly relies on the driver's behaviour of operating the steering wheel. The driving model built in this paper only focuses on the steering behaviour of drivers and the lateral control of host vehicle. The input and output of model are the environmental information $\mathbf{X}_{\mathrm{Env}}$ and the lateral operation of drivers $\mathbf{Y}_{\mathrm{Op}}$, respectively. Following [23], the input $\mathbf{X}_{\mathrm{Env}} = \{\mathbf{X}^t_{\mathrm{Env}}\}^n_{t=1}$ and output $\mathbf{Y}_{\mathrm{Op}} = \{Y^t_{\mathrm{Op}}\}^n_{t=1}$ at time t are defined as follows:

$$\mathbf{X}^t_{\mathrm{Env}} = [\underbrace{x^t_{\mathrm{host}}, y^t_{\mathrm{host}}, h^t_{\mathrm{host}}, \delta^t_{\mathrm{host}}, v^t_{\mathrm{host}},}_{\mathrm{Hostvehicle}} \quad \underbrace{x^t_{\mathrm{Ref}}, y^t_{\mathrm{Ref}}}_{\mathrm{Referencevehicles}} \quad] \tag{1}$$

$$Y^t_{\mathrm{Op}} = \delta^{t+1}_{\mathrm{host}} \tag{2}$$

where x^t_{host} and y^t_{host} are longitudinal and lateral positions of host vehicle at time t, h^t_{host} and δ^t_{host} denote the heading angle and the steering wheel angle of host vehicle. v^t_{host} is the velocity of host vehicle at time t. Analogously, x^t_{Ref} and y^t_{Ref} are longitudinal and lateral positions of reference vehicles. $\delta^{t+1}_{\mathrm{host}}$ is the driver's operation at time $t+1$.

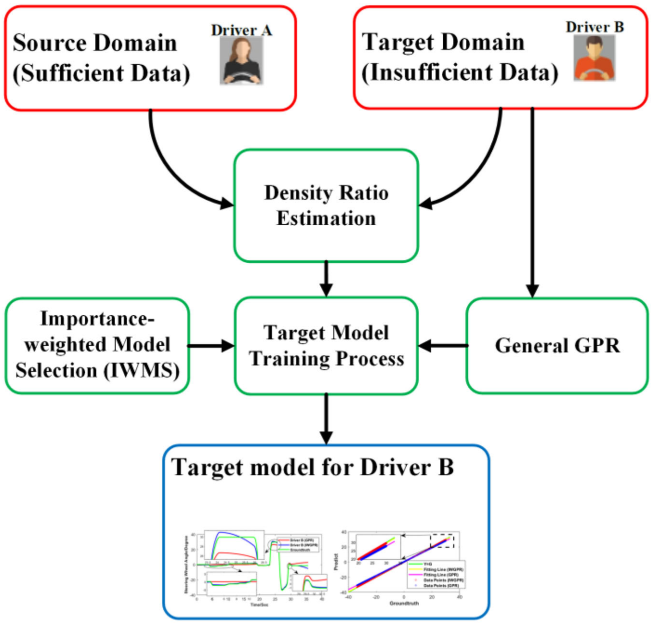


Fig. 2. An illustration of the proposed IWGPR.

The overall illustration of IWGPR is shown in Fig. 2. The whole system consists of four parts: density ratio estimation, importance weighted model selection, general GPR and the training process of target model. The first part, density ratio estimation, provides the ratio of marginal distributions (IW) between data of source and target drivers. Then the prior knowledge of source driver with sufficient data and the specific knowledge of target driver with insufficient data are both embedded in IW, which can be used to formulate the object function for TL. In the target model training process, IW calculated by the first part is combined with the kernel function of general GPR. Knowledge from source and target drivers is reused by the target driver model. Therefore, insufficient data of target driver can be modelled effectively with the help of TL from the source driver. Meanwhile, the model selection based on IW is also developed and applied in the target model, which automatically provides optimal parameters in the training process. Finally, the target model, IWGPR, is built by sufficient source data and insufficient target data.

In order to realise the proposed method above, firstly, the density ratio estimation in TL-based regression is introduced and emphasized, which is the basis of IWGPR. Secondly, with the combination of IW and general GPR, a novel TL-based GPR, IWGPR, is developed and detailed. Thirdly, considering the model selection for hyper-parameters in GPR, an importance weighted model selection method (IWMS) is proposed based on the negative log density loss function.

A. Density Ratio Estimation

Density ratio estimation is applied to calculate the ratio of marginal distributions between insufficient driving data of two drivers. In ML methods with kernels in the objective function, IW calculated by density ratio estimator can be integrated with the kernel function, which provides a novel way to modify the model of target driver by reweighting driving data of source driver.

Unconstrained least-squares importance fitting (ULSIF) is a typical method for estimating the density ratio between distributions of two datasets and has been widely used in model adaptation problems. In this paper, ULSIF is selected to estimate the density ratio between two different drivers. Using ULSIF, the IW estimation problem can be transformed to a quadratic programming (QP) problem, which can be solved by common QP solvers [33].

In the model training process of regression or classification, the optimal model is built by minimising the following expected risk [17]:

$$\theta^* = \arg\min_{\theta\in\Theta} \mathrm{E}_{(x,y)\in P}[l(x,y,\theta)] \tag{3}$$

where $l(x,y,\theta)$ is the loss function with parameter θ. Since it is hard to estimate the probability distribution P, we chose to estimate the empirical risk minimization (ERM) [34]:

$$\theta^* = \arg\min_{\theta\in\Theta} \frac{1}{n}\sum_{i=1}^{n}[l(x_i,y_i,\theta)] \tag{4}$$

where n is the number of training samples. In this research, the optimal model is learnt using insufficient driving data in the target domain:

$$\theta^* = \arg\min_{\theta\in\Theta} \sum_{\boldsymbol{\zeta}\in\mathbf{D}_{\mathrm{T}}} P(\mathbf{D}_{\mathrm{T}})l(\boldsymbol{\zeta}_t,\theta) \tag{5}$$

where $\boldsymbol{\zeta}_t = [\mathbf{X}^t_{\mathrm{Env}}, \delta^{t+1}_{\mathrm{host}}]$ is the combination of the environmental information $\mathbf{X}_{\mathrm{Env}}$ and the driver's lateral operation $\delta^{t+1}_{\mathrm{host}}$, $l(\boldsymbol{\zeta}_t,\theta)$ is the loss of objective function. If $P(\mathbf{D}_{\mathrm{S}}) = P(\mathbf{D}_{\mathrm{T}})$, the model trained from the source domain can be applied in the target domain:

$$\theta^* = \arg\min_{\theta\in\Theta} \sum_{\boldsymbol{\zeta}\in\mathbf{D}_{\mathrm{S}}} P(\mathbf{D}_{\mathrm{S}})l(\boldsymbol{\zeta}_t,\theta) \tag{6}$$

However, an important and fundamental assumption is that distributions of driving data from two drivers are different, $P(\mathbf{D}_{\mathrm{S}}) \neq P(\mathbf{D}_{\mathrm{T}})$. Therefore, directly replacing $P(\mathbf{D}_{\mathrm{T}})$ with $P(\mathbf{D}_{\mathrm{S}})$ is unreasonable and insufficient data cannot successfully build the target model. In order to solve problems above, a rational conversion is operated on the primary objective function (6):

$$\begin{aligned}\boldsymbol{\theta}^* &= \arg\min_{\boldsymbol{\theta}\in\Theta} \sum_{\boldsymbol{\zeta}\in\mathbf{D}_{\mathrm{T}}} \frac{P(\mathbf{D}_{\mathrm{T}})}{P(\mathbf{D}_{\mathrm{S}})} P(\mathbf{D}_{\mathrm{S}})l(\boldsymbol{\zeta}_{\mathrm{T}},\boldsymbol{\theta}) \\ &\approx \arg\min_{\boldsymbol{\theta}\in\Theta} \sum_{i=1}^{n_{\mathrm{s}}} \frac{P_{\mathrm{T}}(\mathbf{X}^i_{\mathrm{Env,T}}, \delta^i_{\mathrm{host,T}})}{P_{\mathrm{S}}(\mathbf{X}^i_{\mathrm{Env,S}}, \delta^i_{\mathrm{host,S}})} \\ &\quad \times P_{\mathrm{S}}(\mathbf{X}^i_{\mathrm{Env,S}}, \delta^i_{\mathrm{host,S}})l(\boldsymbol{\zeta}_{\mathrm{S},i},\boldsymbol{\theta})\end{aligned} \tag{7}$$

With the assumption for transductive TL in [17], $P(\mathbf{Y}_{\mathrm{Op,T}}|\mathbf{X}_{\mathrm{Env,T}}) = P(\mathbf{Y}_{\mathrm{Op,S}}|\mathbf{X}_{\mathrm{Env,S}})$, the following objective function is obtained:

$$\boldsymbol{\theta}^* \approx \arg\min_{\boldsymbol{\theta}\in\Theta} \sum_{i=1}^{n_{\mathrm{s}}} \frac{P_{\mathrm{T}}(\boldsymbol{\zeta}_{\mathrm{T},i})}{P_{\mathrm{S}}(\boldsymbol{\zeta}_{\mathrm{S},i})} P_{\mathrm{S}}(\boldsymbol{\zeta}_{\mathrm{S},i})l(\boldsymbol{\zeta}_{\mathrm{S},i},\boldsymbol{\theta}) \tag{8}$$

Meanwhile, the probability density ratio is

$$\omega = \frac{P_{\mathrm{T}}(\mathbf{X}^i_{\mathrm{Env,T}}, Y^i_{\mathrm{Op,T}})}{P_{\mathrm{S}}(\mathbf{X}^i_{\mathrm{Env,S}}, Y^i_{\mathrm{Op,S}})} = \frac{P_{\mathrm{T}}(\mathbf{X}^i_{\mathrm{Env,T}})}{P_{\mathrm{S}}(\mathbf{X}^i_{\mathrm{Env,S}})} \quad (9)$$

where $\mathbf{X}_{\mathrm{Env}}$ and $\mathbf{Y}_{\mathrm{Op}}$ are the input and output of model. So far, the optimal problem for target driver model is split into two phases: calculating the probability density ratio ω and minimizing the objective function (8).

ULSIF is developed based on the hypothesis that distributions of source and target driving data are independent identically distributed (i.i.d), which can be described as follows:

$$\mathbf{D}_{\mathrm{T}} = \{\mathbf{X}^i_{\mathrm{Env,T}}\}^{N_{\mathrm{T}}}_{i=1} \overset{i,i,d}{\rightarrow} p_{\mathrm{T}}(\mathbf{X}_{\mathrm{Env,T}}) \quad (10)$$

$$\mathbf{D}_{\mathrm{S}} = \{\mathbf{X}^i_{\mathrm{Env,S}}\}^{N_{\mathrm{S}}}_{i=1} \overset{i,i,d}{\rightarrow} p_{\mathrm{S}}(\mathbf{X}_{\mathrm{Env,S}}) \quad (11)$$

where N_{S} and N_{T} is the number of samples collected from source and target driver, respectively.

In order to estimate and describe $\boldsymbol{\omega}$, a linear model is applied:

$$\hat{\boldsymbol{\omega}}(\mathbf{X}_{\mathrm{Env}}) = \Sigma^b_{l=1} \alpha_l \varphi_l(\mathbf{X}_{\mathrm{Env}}) \quad (12)$$

where $\varphi_l(\mathbf{X}_{\mathrm{Env}})$ is the basic function and α_l is the model parameter which can be obtained by the model training process. b and $\varphi_l(\mathbf{X}_{\mathrm{Env}})$ can be calculated by samples from source and target drivers. Here Gaussian kernel is chosen as the basic function. Meanwhile, a part of samples from the target driver is selected as the Gaussian kernel centre. Therefore, the linear model (12) above is modified as:

$$\hat{\boldsymbol{\omega}}(\mathbf{X}_{\mathrm{Env}}) = \Sigma^b_{l=1} \alpha_l K_\sigma(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}^l_{\mathrm{Env,T}}) \quad (13)$$

where $K_\sigma(\cdot)$ is Gaussian kernel function and α_l is the model parameter, with the kernel width σ_σ:

$$K_\sigma(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env,T}}) = \exp\left(-\frac{\|\mathbf{X}_{\mathrm{Env}} - \mathbf{X}_{\mathrm{Env,T}}\|^2}{2{\sigma_\sigma}^2}\right) \quad (14)$$

In the above transformed linear model, model parameters obtained in the model training process can be calculated by the following least-square-based objective function [33]:

$$\begin{aligned} J(\boldsymbol{\alpha}) &= \frac{1}{2}\int (\hat{\boldsymbol{\omega}}(\mathbf{X}_{\mathrm{Env}}) - \boldsymbol{\omega}(\mathbf{X}_{\mathrm{Env}}))^2 p_{\mathrm{tr}}(\mathbf{X}_{\mathrm{Env}}) d\mathbf{x} \\ &= \frac{1}{2}\boldsymbol{\alpha}^{\mathrm{T}} \boldsymbol{H} \alpha - \mathbf{h}^{\mathrm{T}} \boldsymbol{\alpha} + C' \end{aligned} \quad (15)$$

where C' is a constant. $\mathbf{H}$ and $\mathbf{h}$ are the $N_{\mathrm{T}} \times N_{\mathrm{T}}$ matrix and the vector with N_{T} dimensions, which are approximated by following equations:

$$\hat{\mathbf{H}}_{n,n} = \frac{1}{N_{\mathrm{S}}} \sum^{N_{\mathrm{S}}}_{n''} K(\mathbf{X}^{n''}_{\mathrm{Env,S}}, \mathbf{X}^{n''}_{\mathrm{Env,T}}) K(\mathbf{X}^{n''}_{\mathrm{Env,S}}, \mathbf{X}^{n''}_{\mathrm{Env,T}}) \quad (16)$$

$$\hat{\mathbf{h}}_n = \frac{1}{N_{\mathrm{T}}} \sum^{N_{\mathrm{T}}}_{n'=1} K(\mathbf{X}^{n'}_{\mathrm{Env,T}}, \mathbf{X}^n_{\mathrm{Env,T}}) \quad (17)$$

And then the expression for optimal model parameters are as follows:

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \left(\frac{1}{2}\boldsymbol{\alpha}^{\mathrm{T}} \boldsymbol{H} \alpha - \hat{\mathbf{h}}^{\mathbf{T}} \boldsymbol{\alpha} + \frac{\gamma}{2}\boldsymbol{\alpha}^{\mathbf{T}}\boldsymbol{\alpha}\right) \quad (18)$$

where $\frac{\gamma}{2}\boldsymbol{\alpha}^{\mathbf{T}}\boldsymbol{\alpha}$ is the part for L2 regularisation. The above equation is formulated as an unconstrained convex quadratic program (QP). Solving this QP problem, the following analytical solution can be obtained:

$$\hat{\boldsymbol{\alpha}} = (\hat{\mathbf{H}} + \gamma \mathbf{I}_{N_{\mathrm{te}}})\hat{\mathbf{h}} \quad (19)$$

Combined with (12), the final expression of IW-based analytical solution is calculated by:

$$\hat{\boldsymbol{\omega}}(\mathbf{X}_{\mathrm{Env}}) = \max\left(0, \sum^{N_{\mathrm{T}}}_{n=1} \hat{\alpha}_n K_\sigma(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env,T}})\right) \quad (20)$$

B. Transferable Gaussian Process Regression

In order to deal with the problem of modelling with different data distributions for training and test sets, several studies have been done to develop transferable and adaptive GPRs [35]–[37]. However, many of these methods are applied in highly simplified scenarios, and rarely focus on real-world problems involving uncertain human behaviours. The proposed method in this paper considers the density ratio between driving data of different drivers and incorporates the density ratio estimation into GPR, which can model the behaviour of target driver with insufficient driving data by using prior knowledge transferred from the source driver.

The proposed method is developed based on IW, which can be efficiently calculated by density ratio estimators. In the process of IW-based instance level TL, the density ratio ω only describes the relation between two drivers, which cannot be directly applied in the specific scenario. Therefore, inspired by [32], the algorithm proposed in this paper combines GPR with the density ratio, thus developing a novel TL method, IWGPR.

From the view of function space, GP is defined to describe the distribution over functions and operates Bayes inference directly in function space. According to [12], an explicit definition is provided: GP is described as a gather of random variables with joint Gaussian distributions. The characteristic of GP is completely determined by mean function $m(\mathbf{X}_{\mathrm{Env}})$and covariance function $\mathrm{k}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X'}_{\mathrm{Env}})$:

$$m(\mathbf{X}_{\mathrm{Env}}) = \mathrm{E}[f(\mathbf{X}_{\mathrm{Env}})] \quad (21)$$

$$\begin{aligned} &k(\mathbf{X}_{\mathrm{Env}}, \mathbf{X'}_{\mathrm{Env}}) \\ &= \mathrm{E}[(f(\mathbf{X}_{\mathrm{Env}}) - m(\mathbf{X}_{\mathrm{Env}}))(f(\mathbf{X'}_{\mathrm{Env}}) - m(\mathbf{X'}_{\mathrm{Env}}))] \end{aligned} \quad (22)$$

where $\mathbf{X}_{\mathrm{Env}}, \mathbf{X'}_{\mathrm{Env}} \in \mathbf{R}^d$ are the environmental information. With the pre-processing, $m(\mathbf{X}_{\mathrm{Env}})$ is modified as the zero-mean function. Therefore, a simple Gaussian process can be described by:

$$f(\mathbf{X}_{\mathrm{Env}}) \sim GP(m(\mathbf{X}_{\mathrm{Env}}), \mathrm{k}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X'}_{\mathrm{Env}})) \quad (23)$$

With the Gaussian noise $\varepsilon \in N(0, \sigma_n^2)$, the prior distribution of $\mathbf{Y}_{\mathrm{Op}}$ can be obtained and shown as below:

$$\mathbf{Y}_{\mathrm{Op}} \sim N(0, \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) + \sigma_n^2 \mathbf{I}_n) \tag{24}$$

Then, the joint distribution of prediction and observed values can be described by:

$$\begin{bmatrix} \mathbf{Y}_{\mathrm{Op}} \\ f_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) + \sigma_n^2 \mathbf{I}_n & \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, x^*_{\mathrm{Env}}) \\ \mathrm{K}(x^*_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) & \mathrm{K}(x^*_{\mathrm{Env}}, x^*_{\mathrm{Env}}) \end{bmatrix}\right) \tag{25}$$

where $\mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) = \mathrm{K}_n = (\mathrm{k}_{ij})$ is the symmetric positive definite covariance matrix and $\mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) \in \mathbf{R}^{n \times n}$. $k_{ij} = \mathrm{k}(\mathbf{X}^i_{\mathrm{Env}}, \mathbf{X}^j_{\mathrm{Env}})$ is used to measure the correlation between $\mathbf{X}^i_{\mathrm{Env}}$ and $\mathbf{X}^j_{\mathrm{Env}}$. $\mathrm{K}(\mathbf{X}_{\mathrm{Env}}, x^*_{\mathrm{Env}}) = \mathrm{K}(x^*_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}})^{\mathrm{T}}$ is the covariance matrix between test points x_* and the input vector $\mathbf{X}_{\mathrm{Env}}$. $\mathrm{K}(x^*_{\mathrm{Env}}, x^*_{\mathrm{Env}})$ is the covariance matrix of x_* itself and $\mathbf{I}_n \in n \times n$ is the unit matrix. Here we choose Gaussian kernel with width σ_f as the covariance function:

$$\mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X'}_{\mathrm{Env}}) = \exp\left(-\frac{\|\mathbf{X}_{\mathrm{Env}} - \mathbf{X'}_{\mathrm{Env}}\|^2}{2\sigma_f^2}\right) \tag{26}$$

Inspired by IW-based regression and classification methods, the density ratio $\boldsymbol{\omega}$ need to be combined with kernel functions in GPR. By embodying $\boldsymbol{\omega}$ in kernel functions, the prior knowledge from source driver can be reflected in the target model. Therefore, the distribution of modified GPR is as follow:

$$\mathbf{Y}_{\mathrm{Op}} \sim N(0, \mathbf{K}_{\mathrm{Transfer}} \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) + \sigma_n^2 \mathbf{I}_n) \tag{27}$$

For the above equation, the Gaussian noise assumption$\varepsilon \in N(0, \sigma_n^2)$ is similar to general GPR. Meanwhile, the joint distribution of observed values $\mathbf{Y}_{\mathrm{Op}}$ and predictions f_* for IWGPR is modified as:

$$\begin{bmatrix} \mathbf{Y}_{\mathrm{Op}} \\ f_* \end{bmatrix} \sim N \times \left(0, \begin{bmatrix} \mathbf{K}_{\mathrm{Transfer}} \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) + \sigma_n^2 \mathbf{I}_n & \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, x^*_{\mathrm{Env}}) \\ \mathrm{K}(x^*_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) & \mathrm{K}(x^*_{\mathrm{Env}}, x^*_{\mathrm{Env}}) \end{bmatrix}\right) \tag{28}$$

Let

$$\mathbf{K}_{\mathrm{Transfer}} = \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \boldsymbol{X}_{\mathrm{Env}})^{\mathrm{T}} \boldsymbol{\omega}^{\upsilon} = \begin{pmatrix} (\mathrm{k}_{11}) & \cdots & (\mathrm{k}_{1i}) \\ \vdots & \ddots & \vdots \\ (\mathrm{k}_{i1}) & \cdots & (\mathrm{k}_{ii}) \end{pmatrix} \begin{pmatrix} \hat{\omega}_1^{\upsilon} & \cdots & \hat{\omega}_1^{\upsilon} \\ \vdots & \ddots & \vdots \\ \hat{\omega}_i^{\upsilon} & \cdots & \hat{\omega}_i^{\upsilon} \end{pmatrix} \tag{29}$$

The joint distribution between $\mathbf{Y}_{\mathrm{Op}}$ and f_* is combined with the density ratio $\boldsymbol{\omega}$, which indicates that the prior knowledge from source driver is considered in specific problems of target driver. With the help of samples from the source driver, the joint distribution of driving data can accurately describe characteristics of the target model. The posterior distribution of prediction is calculated:

$$f_* | \mathbf{X}_{\mathrm{Env}}, \mathbf{Y}_{\mathrm{Op}}, x^*_{\mathrm{Env}} \sim N(\bar{f}_*, \mathrm{cov}(f_*)) \tag{30}$$

Finally, the mean prediction value and covariance of IWGPR are deduced:

$$\bar{f}_* = \mathrm{K}(x^*_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) \times [\mathbf{K}_{\mathrm{Transfer}} \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) + \sigma_n^2 \mathbf{I}_n]^{-1} \mathrm{K}_{\mathrm{T}} \mathbf{Y}_{\mathrm{Op}} \tag{31}$$

$$\mathrm{cov}(f_*) = \mathrm{K}(x^*_{\mathrm{Env}}, x^*_{\mathrm{Env}}) - \mathrm{K}(x^*_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) \mathbf{K}_{\mathrm{Transfer}} \times [\mathbf{K}_{\mathrm{Transfer}} \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, \mathbf{X}_{\mathrm{Env}}) + \sigma_n^2 \mathbf{I}_n]^{-1} \times \mathbf{K}_{\mathrm{Transfer}} \mathrm{K}(\mathbf{X}_{\mathrm{Env}}, x^*_{\mathrm{Env}}) \tag{32}$$

III. Importance Weighted Model Selection (IWMS)

In order to realise and apply IWGPR in specific scenarios, parameters of IWGPR need to be determined in the model training and model selection process. Each kernel has its own parameters independently. For the proposed method in this paper, undetermined parameters are as follows: Gaussian noise parameter σ_n, Gaussian kernel width σ_f and the level of IW υ.

Cross validation (CV) is a common and effective method for model selection (MS), which randomly divides whole training data into K folds and leaves one fold out for test [38]. Considering that the target of TL is to transfer the instance level knowledge from source driver to target driver, the density ratio $\boldsymbol{\omega}$ of two datasets needs to be taken into account [39]. In this paper, based on CV, IWGPR considers the IW in MS. It can be described as follow:

$$W_{\mathrm{IWCV}} = \frac{1}{K} \sum_{k=1}^{K} \frac{1}{|\mathbf{D}_{\mathrm{S},k}|} \sum_{(\boldsymbol{\zeta}_S \in \mathbf{D}_{\mathrm{S},k})} \boldsymbol{\omega}(\mathbf{X}_{\mathrm{Env,S}}) \times loss(\hat{f}_k(\mathbf{X}_{\mathrm{Env,S}}), \mathbf{Y}_{\mathrm{Op,S}}) \tag{33}$$

where K is the number of folds in K-fold CV. $\boldsymbol{\omega}(\mathbf{s}_S)$is the density ratio and $loss(\cdot)$is the loss function which is given by:

$$loss(\cdot) = \log p(\mathbf{Y}^i_{\mathrm{Op}} | \mathbf{X}^i_{\mathrm{Env}}, \mathbf{Y}^{-i}_{\mathrm{Op}}, \boldsymbol{\theta}) = \frac{1}{2} \log \mathrm{cov}(f_{*,i})^2_i + \frac{(\mathbf{Y}^i_{\mathrm{Op}} - f_{*,i})^2}{2\mathrm{cov}(f_{*,i})^2_i} + \frac{1}{2} \log 2\pi \tag{34}$$

Finally, the IW-based model selection process (IWMS) obtains optimal parameters by:

$$(\hat{\sigma}_f, \hat{\sigma}_n, \hat{\upsilon}) = \underset{(\sigma_f, \sigma_n, \upsilon)}{\arg\min}\, W_{\mathrm{IWMS}}(\sigma_f, \sigma_n, \upsilon) \tag{35}$$

When the proposed method unites ULSIF, IWGPR and IWMS, the integrated system is shown by pseudo code.

IV. Experiments and Analysis

In order to highlight basic characteristics of IWGPR and test the performance of proposed algorithm, four experiments are designed, including one experiment for a toy regression problem (Experiment I), one experiment using data collected from a driving simulator (Experiment II), one experiment using driving data of UAH-DriveSet (Experiment III), and the final

Algorithm 1: IWGPR.

Input: $\{\mathbf{X}^j_{\text{Env,S}}\}^{N_\text{S}}_{j=1}, \{\mathbf{X}^j_{\text{Env,S}}\}^{N_\text{T}}_{j=1}, \{\mathbf{Y}^j_{\text{Op,S}}\}^{N_\text{S}}_{j=1}$
Output: mean $\bar{f}_*$, variance $V[\bar{f}_*]$

Calculate $\hat{\mathbf{H}}_{n,n}$ and $\hat{\mathbf{h}}_n$ by (16) and (17)
Obtain the optimal model parameter $\hat{\boldsymbol{\alpha}}$ in (12) by (19)
Obtain $\hat{\boldsymbol{\omega}}^v = uLSIF(\{\mathbf{X}^j_{\text{Env,S}}\}^{N_\text{T}}_{j=1}, \{\mathbf{X}^j_{\text{Env,S}}\}^{N_\text{S}}_{j=1})$ by (20)
for each candidate of σ_f **do**
  for each candidate of $\hat{v}$ **do**
    for each candidate of σ_n **do**
      Calculate $\mathrm{K}(\mathbf{X}_{\text{Env}}, \mathbf{X}_{\text{Env}})$ by (26)
      Calculate $\mathbf{K}_{\text{Transfer}}$ by (29)
      $\mathbf{L} = cholesky(\mathbf{K}_{\text{Transfer}}\mathrm{K}(\mathbf{X}_{\text{Env}}, \mathbf{X}_{\text{Env}}) + \sigma_n^2\mathbf{I}_n)$
       $\alpha = \mathbf{L}^{\text{T}} \backslash (\mathbf{L} \backslash \mathbf{K}_{\text{T}}\mathbf{Y}_{\text{Op,S}})$
       Get the $\bar{f}_*$ and $V[f_*]$ by (30∼32)
       Obtain the $loss(\cdot)$ by (34)
       Calculate the total loss W_{IWCV} in each episode by (33)
    end for
  end for
end for
Obtain optimal parameters $\hat{\sigma}_f$, $\hat{v}$, $\hat{\sigma}_n$ by (35)
Get $\hat{\boldsymbol{K}}_{\hat{\sigma}_f}$ and $\hat{\mathbf{K}}_{\text{Transfer}(\hat{\sigma}_f, \hat{v}, \hat{\sigma}_n)}$ by (26) and (29)
Get the output $\bar{f}$ and $\bar{V}[f_*]$ by (31) $\sim$ (32)
return mean $\bar{f}_*$, variance $V[\bar{f}_*]$

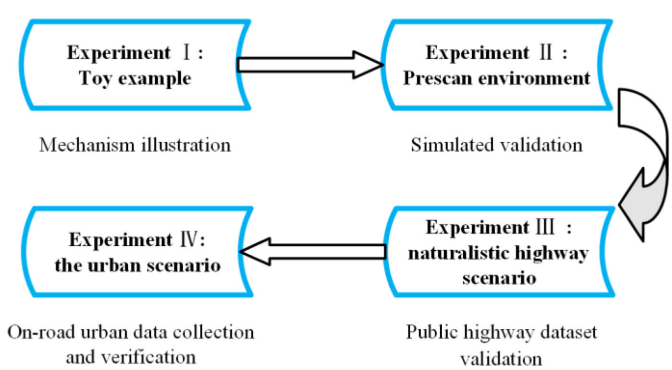


Fig. 3. Relationship between four experiments.

experiment using naturalistic driving data collected in the urban traffic scenario (Experiment IV).

In Experiment I, a simple toy regression problem is selected to show basic characteristics and mechanism of IWGPR. Then, based on the mechanism observed from Experiment I, three experiments with different data sources are designed to test the model performance and adaptability of IWGPR in the lane change scenario. Details of four experiments and relevant analysis are shown in following four subsections. The relationships between four experiments are shown in Fig. 3.

A. Experiment I: Toy Regression Problem

In order to illustrate the effectiveness and mechanism of proposed method, firstly, two readily comprehensible datasets

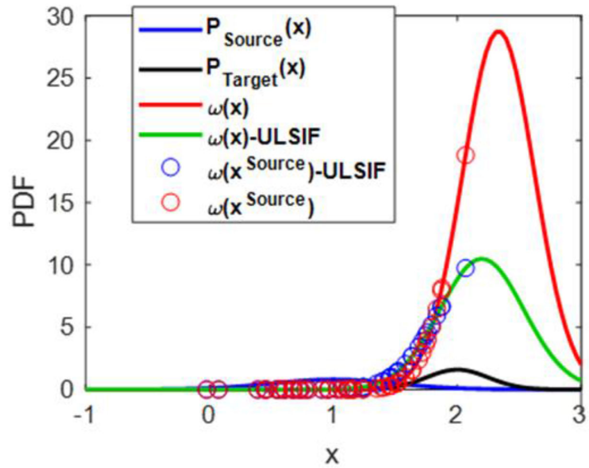


Fig. 4. Different distributions of two datasets and the estimation of density ratio. (Green line: estimation, red line: groundtruth, blue line: the distribution of the source dataset, black line: the distribution of the target dataset).

following different distributions with one-dimension are used. Following [32], [33], datasets with known distributions is used to verify the proposed method in Experiment I.

Firstly, let densities of source and target datasets follow two distributions:

$$P_{\text{Source}}(\mathbf{x}) = \phi\left(\mathbf{x}; 1, \left(\frac{1}{2}\right)^2\right) \tag{36}$$

$$P_{\text{Target}}(\mathbf{x}) = \phi\left(x; 2, \left(\frac{1}{4}\right)^2\right) \tag{37}$$

where $\phi(x; \mu, \sigma^2)$ is the normal distribution with variance σ^2 and mean μ. Detailed distributions of $P_{\text{Source}}(x)$ and $P_{\text{Target}}(x)$ are shown in Fig. 4 (blue and black), respectively. The target function $f(x)$ is $\sin x$. The relationship between input x and output y is as follow:

$$y = f(x) + \varepsilon \tag{38}$$

where $\varepsilon = \phi(\varepsilon; 0, (\frac{1}{4})^2)$. Set the number of source and target samples as 50 and 1000, respectively.

Fig. 4 shows the performance of density ratio estimation. $P_{\text{Source}}(x)$ and $P_{\text{Target}}(x)$ are distributions of data in source and target datasets. $\omega(x)$ is the ground truth density ratio, while $\omega(x) - ULSIF$ is the density ratio calculated by ULSIF. Comparing IWGPR with GPR, results in Fig. 5 and Fig. 6 indicate that IWGPR can fit noisy toy data with a higher accuracy than GPR. It demonstrates the positive effect of IW from the source dataset.

B. Experiment II: Application on the Lane Change Scenario-Simulated Driving Data

1) Data Collection: The target of proposed method (IWGPR) is to transfer knowledge at the instance level from the source driver (sufficient data) to the target driver (insufficient data) and solve the specific problem for the target driver by building an integrated target model based on GPR. The lane

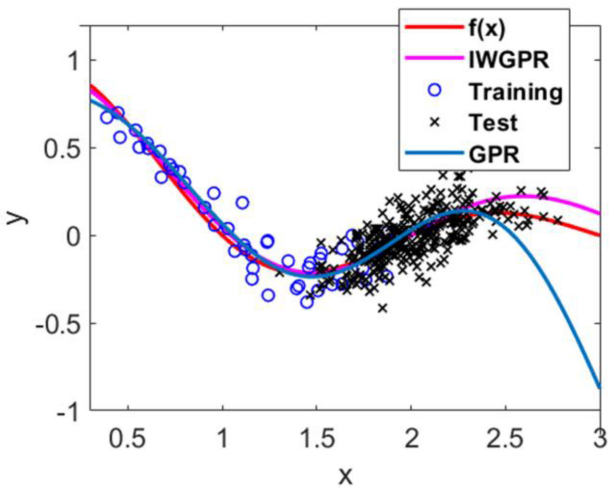


Fig. 5. Fitting results of samples in the target dataset. (Red line: groundtruth, pink line: IWGPR, blue line: GPR).

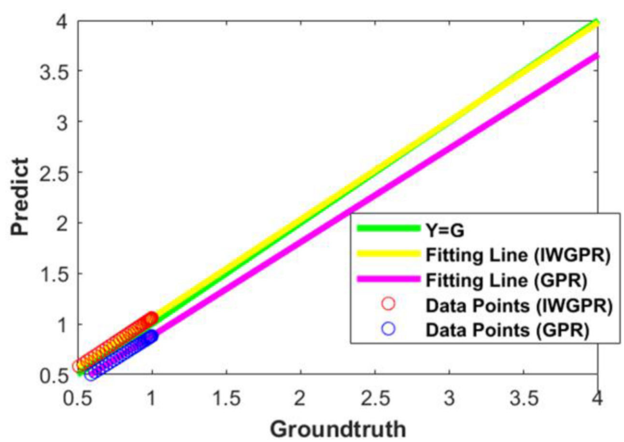


Fig. 6. The comparison of regression performance for IWGPR and GPR (Groundtruth: test samples generated in the toy experiment, Predict: outputs of different methods).

change scenario with one front reference vehicle is chosen for the application and the driver's operation for steering wheel is selected as the action $\mathbf{Y}_{\mathrm{Op}}$. The driver model is built to imitate the human driver's operating process from state to action in the specific scenario. A series of experiments are designed to validate the effect of IWGPR, considering that different drivers have different driving characteristics during the lane-changing which can be presented by distributions of driving data. For example, as to an identical lane change, steering wheel trajectories of two different drivers are distinct obviously (Fig. 8). The lane change scenario is shown in Fig. 1.

Collecting driving data of serval drivers for model training process of IWGPR is the first step where the Prescan/Simulink simulation platform is used. In order to accomplish human-vehicle-road close-loop, Logitech G29 is equipped to collect the human drivers' operations for steering wheel and three screens are applied to provide the view of driving condition to drivers. In the experiment, drivers in the host vehicle are asked to accomplish the whole lane change operation according to their

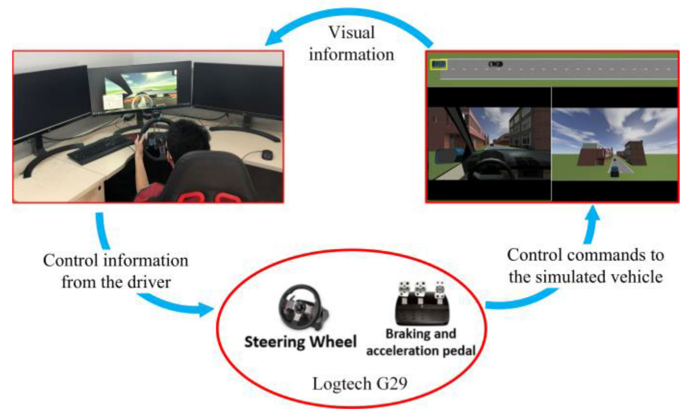


Fig. 7. The driving simulator for data collection.

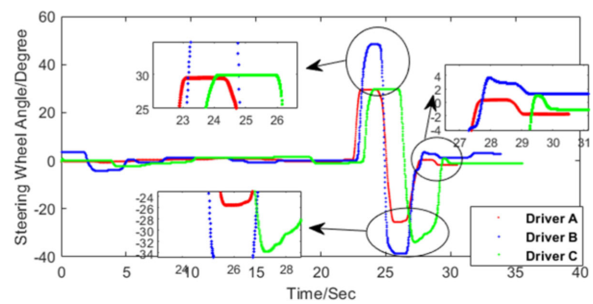


Fig. 8. The comparison for different drivers with steering wheel angle.

own driving styles and judgements by considering states of host and reference vehicles.

2) Analysis of Different Drivers: The proposed TL-based GPR is built on a basic assumption: source and target drivers have different characteristics. As for the specific lane change scenario, different drivers present different driving characteristics on the same condition. A primary comparison is shown in Fig. 9.

In the lane change scenario above, under the same driving environment, three drivers operate the steering wheel to realize the lateral control of vehicle according to their own driving experience. As a whole, for the trajectory of steering wheel which can directly reflect operations of drivers, different drivers perform different behaviours under the same driving condition. For the detailed comparison in 22∼26s, 26∼28s and 28∼29s, there exists evident difference for three drivers. From the view of trajectory, three drivers can be easily distinguished (Fig. 9).

3) Baseline Methods and Metric: In order to compare the proposed algorithm with our previous methods in transferable driver behaviour modelling. Balance distribution adaptation (BDA) is selected for the comparative study. while IWGPR only models the marginal distribution in (7-9), BDA considers both conditional and marginal distributions in the modelling process.

$$\begin{aligned} D(\mathbf{D}_{\mathrm{T}}, \mathbf{D}_{\mathrm{S}}) \approx & (1-\mu) D_1(P(\mathbf{X}_{\mathrm{Env,T}}), P(\mathbf{X}_{\mathrm{Env,S}})) \\ & + \mu D_2(P(\mathbf{Y}_{\mathrm{Op,S}}|\mathbf{X}_{\mathrm{Env,T}}), P(\mathbf{Y}_{\mathrm{Op,T}}|\mathbf{X}_{\mathrm{Env,S}})) \end{aligned} \tag{39}$$

whereD_1 and D_2 represent distances for marginal and conditional distributions, respectively. The distance D is measured

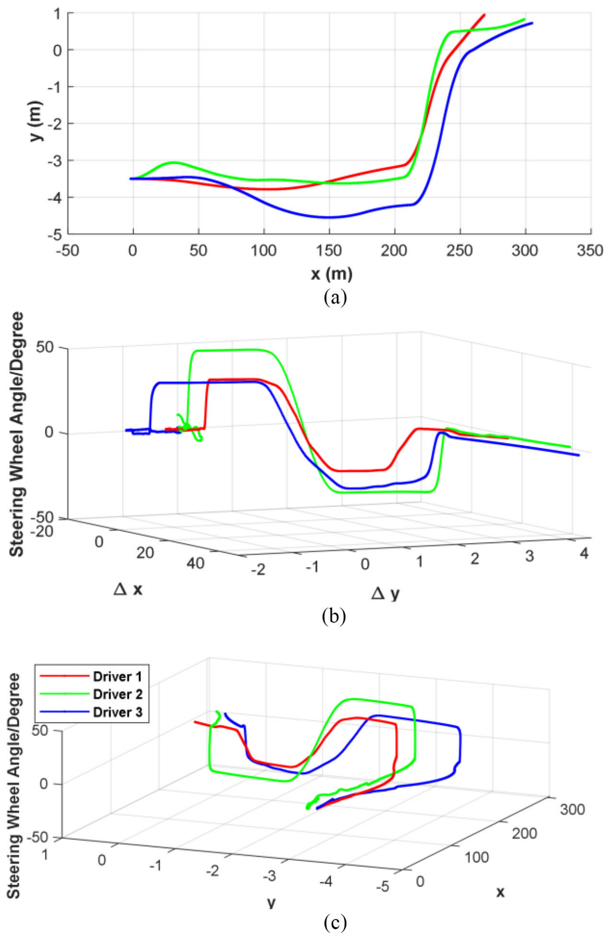


Fig. 9. The comparison of different drivers from different aspects.

by maximum mean discrepancy (MMD) in reproducing kernel Hilbert space (RKHS).

In order to evaluate the performance of target driver model, two indexes are used: mean squared error (MSE) and signal to deviation ratio (SDR).

$$MSE = \frac{1}{N^{\text{test}}} \sum_{i=1}^{N^{\text{test}}} (\hat{y}_i - y_i)^2 \tag{40}$$

$$SDR = \log \frac{\Sigma_{i=1}^{N^{\text{test}}} y_i^2}{\Sigma_{i=1}^{N^{\text{test}}} (\hat{y}_i - y_i)^2} \tag{41}$$

4) Results of TL: After data collection and analysis of different distributions, driving data of three drivers, namely driver A, B and C, are selected for the presentation of TL results. Similar experiments are carried out between every two drivers (A&B, B&C, C&A). For purpose of presenting the effectiveness of IWGPR, between every two drivers, two TL experiments are carried out ($A \to B$, $B \to A$, $B \to C$, $C \to B$, $C \to A$, $A \to C$).

Aggregate results are shown in Table I. As for a better demonstration, TL results from driver A to driver B are detailed, which include a continuous prediction of steering wheel angle with different abscissas, the performance of regression results by coefficient of determination and comparison for different methods. The discussion of detailed results is presented in the next part.

5) Results Discussion: According to TL results from driver A to driver B, in general, as training data of target driver increasing from 40 to 250, MSE decreases and SDR increases for both IWGPR and GPR (IWGPR-MSE: 10.1 to 1.9 deg^2, IWGPR-SDR: 15.3 to 23.3 dB, GPR- MSE: 15.4 to 3.4 deg^2, GPR- SDR: 10.7 to 20.0 dB). It indicates that sufficient data from target driver is conducive to improve the performance of IWGPR with sufficient data from source driver.

Comparing predicting results of GPR using target data with IWGPR proposed in this paper, the performance of IWGPR is better than GPR. The MSE gap of both models decreases from 5.3191 to 1.5651 deg^2 with training data of target driver increasing from 40 to 250 (with SDR gap from 4.6692 to 3.2397 deg^2). The gap between two models is filled gradually, which shows that the superiority of IWGPR is distinct with a small number of training data from the target driver. IWGPR can contribute a better target model comparing to GPR without TL.

IWGPR is a GPR model with the ability of TL. In order to demonstrate the performance of prediction in regression, the case of continuous test points from the target driver is selected for detailed presentation with the situation of N = 250 in Fig. 11. With N = 250, the accuracy of GPR is relatively high for the trajectory of steering wheel angle. Meanwhile, the proposed TL method, IWGPR, has a better performance at time 4∼11s, 23∼26s and 29∼30s, which reflects the effect of prior knowledge from the source driver (driver A). Fig. 13(a) and (b) present trajectories of steering wheel angle relative to positions of host vehicle.

Fig. 12 presents the performance of linear regression with N = 250. Comparing to GPR, fitting results of IWGPR are more similar to ground truth (Y = G), which intuitively illustrates superiority of IWGPR. The same conclusion can also be discovered in Fig. 11. As shown in Table II, comparative results of training and testing time for three methods are detailed. The training time of IWGPR includes the process of density ratio estimation, and the time cost of two distributions adaptation is also contained in the training time. BDA obtains the fastest speed in the test and the shortest in training, while IWGPR presents a poor performance in time consumption. Compared to the regression process of GPR, Gaussian mixture regression (GMR) used in BDA has a better performance in time cost.

Fig. 10(a) and (b) also shows the comparison between IWGPR and BDA, which are both TL-based algorithms for driver behaviour modelling. With the increasing of target samples, MSE of both methods decrease and are lower than general GPR (without TL), which demonstrates the positive effect of TL. And the error gap of BDA and IWGPR is lower than 1 deg^2 with a slight fluctuation. It indicates that although BDA considers the conditional distribution compared to IWGPR, the improvement in prediction is not reflected observably.

C. Experiment III: Application on the Lane Change Scenario—UAH-DriveSet

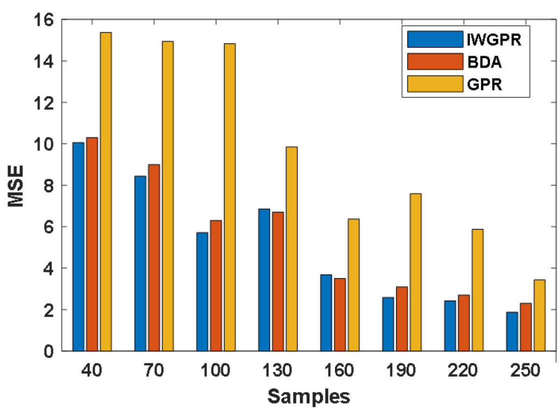
1) The Description of Naturalistic Data: Above experiments in Section IV.A and Section IV.B verify the proposed algorithm

TABLE I
EXPERIMENTAL RESULTS FOR SIMULATED DRIVING DATA (EXPERIMENT II)

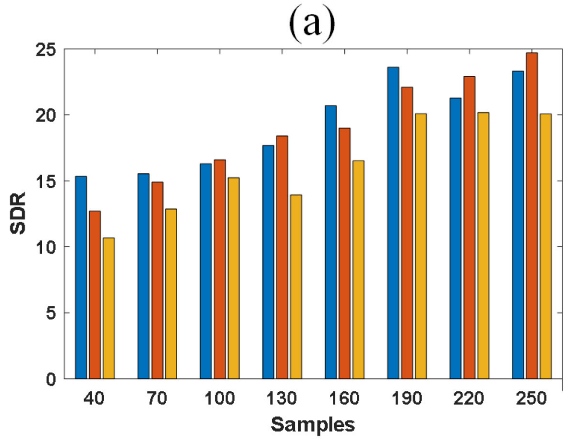
The Number of Training Samples	40		70		100		130		160		190		220		250	
	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR
IWGPR(C to A)	12.6	14.7	10.9	15.4	**5.9**	**19.3**	**4.5**	18.8	4.5	18.9	5.8	20.8	3.2	21.2	4.2	22.6
IWGPR(B to A)	11.3	13.2	11.0	15.7	7.1	15.8	7.6	18.3	5.6	21.5	**3.7**	24.5	2.5	25.1	**2.0**	25.8
BDA(C to A)	**11.2**	**15.1**	**9.5**	15.8	6.9	17.3	5.2	18.0	4.8	19.9	3.9	**25.3**	**2.3**	**26**	2.5	**26.2**
BDA(B to A)	12.0	14.5	10.1	**15.9**	7.2	16.2	6.1	**19.1**	**4.2**	**22.3**	4.3	23.4	3.1	24.1	2.8	14.9
GPR (A)	17.9	9.3	15.5	13.2	11.7	12.3	12.6	15.4	7.0	17.5	4.4	19.5	5.6	19.4	3.5	21.4
IWGPR(C to B)	13.1	12.0	10.2	14.2	8.1	15.1	**6.3**	**19.3**	4.2	**22.1**	4.2	22.4	3.1	**23.4**	3.0	24.9
IWGPR(A to B)	10.1	**15.3**	**8.4**	15.5	**5.7**	16.3	6.8	17.6	3.7	20.6	2.6	23.7	2.4	21.3	**1.9**	23.3
BDA(C to B)	**9.2**	14.3	9.3	**16.1**	7.2	**17.1**	6.5	**19.3**	4.0	21.2	**2.1**	**24.3**	**1.8**	22.4	2.0	**25.0**
BDA(A to B)	10.3	12.7	9.0	14.9	6.3	16.6	6.7	18.4	**3.5**	19.0	3.1	22.1	2.7	22.9	2.3	24.7
GPR (B)	15.4	10.7	14.9	12.8	14.8	15.2	9.8	13.9	6.4	16.5	7.6	20.1	5.8	20.2	3.4	20.0
IWGPR(A to C)	14.3	10.2	11.2	**15.3**	**7.4**	**17.4**	**7.3**	**19.3**	**3.3**	18.2	4.1	**23.1**	**2.1**	**23.2**	2.2	22.3
IWGPR(B to C)	14.2	12.1	9.2	13.1	10.1	17.2	8.1	16.2	4.3	**20.2**	**3.2**	22.1	3.3	23.0	2.1	23.1
BDA(A to C)	**13.7**	11.9	**8.3**	14.0	8.0	16.3	7.5	17.8	4.1	19.5	3.9	21.7	2.8	22.1	**1.9**	**23.4**
BDA(B to C)	14.1	**13.3**	9.3	15.1	9.1	16.2	7.7	17.8	4.0	18.4	4.1	20.0	2.6	19.3	2.5	22.1
GPR (C)	20.1	9.6	16.2	11.2	14.6	11.5	9.0	14.5	8.4	13.1	6.6	18.8	3.9	18.1	4.8	20.2

TABLE II
COMPARATIVE RESULTS OF TRAINING AND TEST TIME

Method	Training time (s)	Testing time (Obs/s)
IWGPR	33.1	~650
GPR	26.8	~700
BDA	12.3	~3100



(a)



(b)

Fig. 10. The MSE and SDR for IWGPR and GPR from driver A to driver B (Simulated driving data).

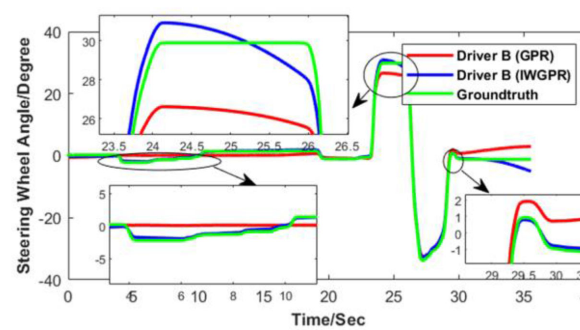


Fig. 11. The comparison for different methods withcontinuous test points (Trajectories of steering wheel).

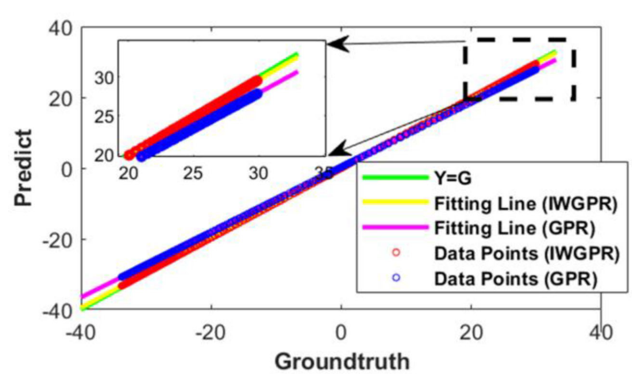


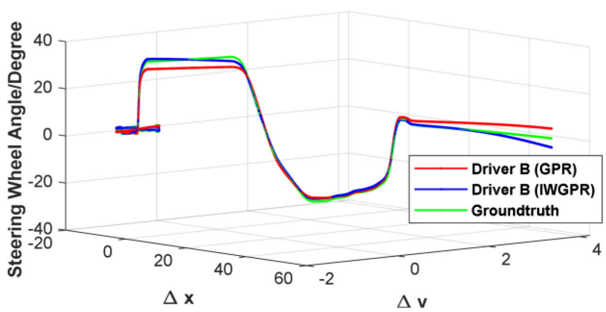
Fig. 12. The comparison of regression performance for IWGPR and GPR.

IWGPR by the toy example and simulated driving data. Compared to naturalistic driving data, driving data collected in the simulated environment are ideal without noise, which cannot fully describe the driver's lane change behaviour in the real and complicated road conditions. Therefore, UAH-DriveSet is applied to verify the proposed algorithm.

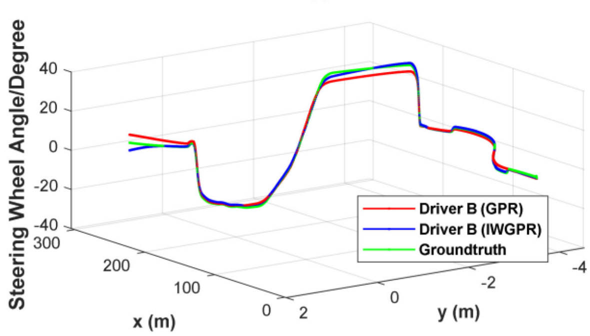
UAH-DriveSet covers driving data of six different drivers with different vehicles (Mercedes, Audi, etc.), two road conditions (motor-way and secondary road) and three different driver styles

TABLE III
EXPERIMENTAL RESULTS FOR NATURALISTIC DRIVING DATA IN THE HIGHWAY SCENARIO (EXPERIMENT III)

The Number of Training Samples	10		20		30		40		50		60		70		80	
	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR
IWGPR(C to A)	0.68	4.35	0.45	4.79	0.33	**5.73**	**0.30**	**8.97**	0.31	7.07	0.19	9.77	0.19	10.8	0.12	10.6
IWGPR(B to A)	0.74	3.81	0.39	4.95	0.39	3.87	0.34	5.22	0.15	**10.5**	0.20	11.8	0.14	12.2	**0.07**	**13.5**
BDA(C to A)	**0.61**	4.87	0.41	**5.49**	0.28	5.39	0.33	7.61	0.19	9.13	0.22	**12.2**	0.18	11.8	0.14	12.8
BDA(B to A)	0.72	**5.01**	**0.33**	5.12	**0.17**	5.57	0.39	6.34	**0.14**	10.1	0.23	10.9	**0.13**	**13.2**	0.12	13.1
GPR (A)	1.02	0.90	0.82	1.73	0.42	2.66	0.45	2.32	0.22	3.86	**0.13**	6.27	0.14	7.89	0.15	9.34
IWGPR(C to B)	0.81	3.03	**0.29**	3.10	0.32	**4.32**	0.29	7.01	0.26	7.37	0.13	10.3	0.10	**12.1**	**0.06**	12.2
IWGPR(A to B)	0.72	1.16	0.40	2.12	0.41	3.15	**0.21**	5.30	0.23	7.21	0.10	7.64	0.11	9.30	**0.06**	10.1
BDA(C to B)	**0.63**	**3.25**	0.51	**3.83**	0.28	4.16	0.30	5.94	0.20	7.90	0.17	8.55	0.09	10.4	0.13	**12.5**
BDA(A to B)	0.75	2.89	0.38	3.43	**0.23**	**4.32**	0.25	**6.10**	**0.18**	**8.37**	**0.09**	**9.53**	**0.07**	9.74	0.08	10.6
GPR (B)	1.13	1.36	0.67	2.98	0.69	3.07	0.63	3.82	0.31	3.84	0.29	6.56	0.20	8.09	0.11	10.7
IWGPR(A to C)	0.61	4.12	0.55	3.32	**0.32**	5.48	**0.25**	**8.27**	0.23	8.26	0.22	9.11	0.22	11.2	0.11	12.3
IWGPR(B to C)	0.65	2.30	0.52	4.35	0.47	5.11	0.32	6.06	0.31	6.14	0.21	7.15	0.16	8.21	0.12	8.25
BDA(A to C)	0.77	3.11	**0.46**	**4.55**	0.37	6.31	0.41	6.58	0.27	8.45	**0.18**	8.79	**0.14**	10.1	0.10	11.7
BDA(B to C)	**0.58**	**4.65**	0.49	4.12	0.35	**6.8**	0.30	7.15	**0.14**	**9.27**	0.25	**10.0**	0.17	**11.9**	0.08	**12.4**
GPR (C)	0.83	1.95	0.72	1.88	0.70	3.25	0.51	3.28	0.31	3.64	0.26	6.08	0.24	7.07	**0.07**	10.7



(a)



(b)

Fig. 13. The comparison for different methods with a continuous test points from different aspects.

TABLE IV
AN ILLUSTRATION OF COLLECTED DATA

Item	Illustration
GPS	Latitude, longitude, Course, Timestamp.
Accelerometers	Acceleration, Acceleration with Kalman Filter, Timestamp.
Processed data (vehicle detection)	Distance to ahead vehicle in the same lane, Time of impact to ahead vehicle, Number of detected vehicles in this frame, Timestamp.

Fig. 14. The interface of playback software for naturalistic driving data [39].

(normal, drowsy and aggressive). Types of collected data are shown in Table IV. The interface of the playback software is shown in Fig. 14. The detailed description of drivers and vehicles involved in the UAH-DriveSet can be found in [39]. For the lane change scenario, useful driving data are cut out manually from the whole dataset. Collected data in UAH-DriveSet are partially missing, so the pre-processing is conducted for naturalistic driving data to satisfy requirements of the modelling process, which is accomplished by the interpolation method and the moving average filter. Meanwhile, the steering wheel angle is not recorded in UAH dataset and the front wheel angle is selected as the output of model.

2) Results and Discussion: Similarly, with experiments in Section IV.B, the number of samples from the target driver is changed to describe and compare the performance of IWGPR. In this experiment, the variation of samples from the target driver ranges from 10 to 80. Experimental results are shown in Table IV. Compared to the general GPR, IWGPR performs better with the number of samples changing from 10 to 40. With

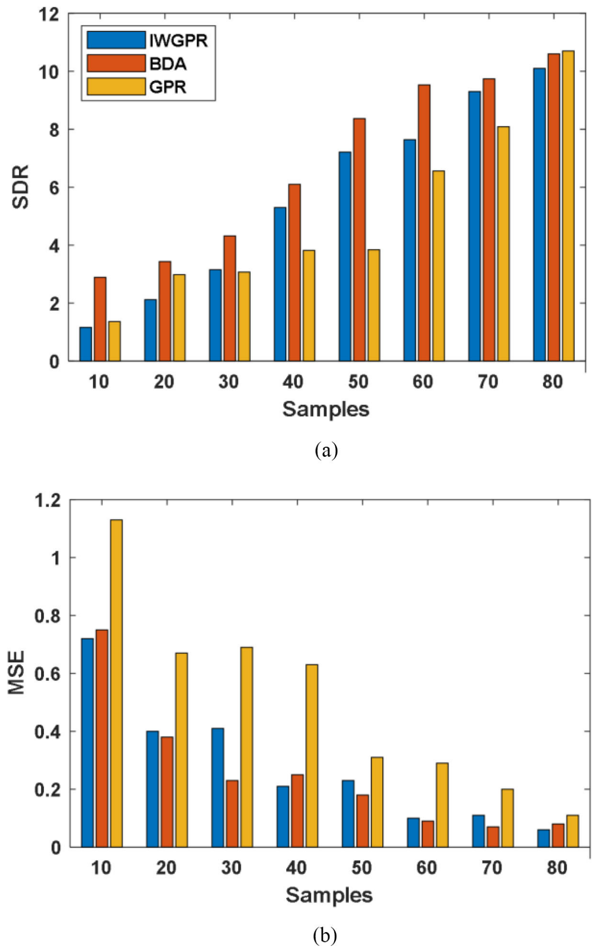


Fig. 15. The SDR and MSE for IWGPR and GPR from driver A to driver B (Naturalistic driving data).

samples of target driver increasing from 50 to 80, the gap of error between general GPR and IWGPR decreases gradually. Both results indicate that Experiment III verifies the conclusion in Experiment II. Beside simulated driving data, the experiment with naturalistic driving data is also conducted to verify IWGPR, which reflects the adaptability of proposed algorithm.

As for naturalistic driving data, results in Fig. 15(a) and (b) indicate that even if with relative more target samples, the performance of IWGPR is better than general GPR. It illustrates that the TL-based method utilizes the prior knowledge from the source driver (driver A). Data collected from source driver in the lane change scenario improve the performance of target driver model, which verifies the positive effect of TL in the driver specific-behaviour learning. Although the experiment based on naturalistic driving data cannot obtain ideal results in some special cases (N = 20 in Fig. 15), overall results still show the improvement of TL compared to the non-TL method. Non-ideal situations that the TL method cannot reflect the effect may be caused by the noise in mobile-based data collection process. As for the comparison of IWGPR and BDA in Fig. 15(a) and (b), the performance in MSE is same as that in Experiment II. However, the SDR of BDA is higher than IWGPR, which presents a better performance of fluctuation in prediction.

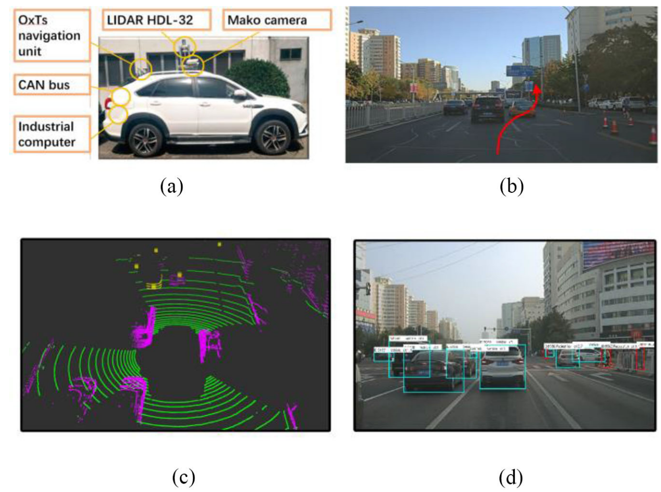


Fig. 16. (a) The sensor equioment on the intelligent vehicle platform. (b) The urban scenario for naturalistic data collection. (Red line: the schematic trajectory of right lane-changing). (c) The illustration of detection from point cloud. (d) The fusion result of Lidar and camera.

D. Experiment IV: Application in the Urban Lane-Changing Scenario

Scenarios extracted from UAH-DriveSet are high-speed Lane-changing behaviours, which mainly occur in the highway. And operations $\mathbf{Y}_{\mathrm{Op}} = \{Y^t_{\mathrm{Op}}\}^n_{t=1}$ in Experiment III are deduced from trajectories of vehicles, which are different from driver operations collected from CAN bus. In order to fully verify the performance of IWGPR, naturalistic driving data collected in the urban scenario are applied in Experiment IV.

1) Data collection and Pre-Process: Similar to [40], the intelligent vehicle platform for data collection is shown in Fig. 16. The equipment of sensors is detailed as follows:

- OxTs integrated navigation unit: The information of navigation unit includes latitude and longitude, heading angle and longitudinal velocity.
- BYD CAN bus network: The vehicle CAN bus network provides steering wheel angle.
- Two Mako cameras: The camera provides the front vision of vehicle.
- Velodyne Lidar HDL-32E: Lidar is applied to detected surrounding vehicles by fusing the information from camera.

In Experiment IV, three drivers with different driving experience participate the data collection in the urban scenario (Beijing, China). In order to extract the lane-changing scenario, collected data is pre-processed and selected manually. Moving average filter (MAF) is applied to smooth driving data with filter window size $W = 4$.

2) Experimental Results and Discussion: Experimental results are shown in Table V. With the increasing of samples in the target domain, comparative results of IWGPR and two baseline methods are detailed in Fig. 17. Similar to the trend in Experiment II and Experiment III, MSE of three methods decrease when the number of target samples increase from 10 to 80.

Compared to general GPR, IWGPR performs better with different samples. The gap of error between IWGPR and GPR

TABLE V
EXPERIMENTAL RESULTS FOR NATURALISTIC DRIVING DATA IN THE URBAN SCENARIO (EXPERIMENT IV)

The Number of Training Samples	10		20		30		40		50		60		70		80	
	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR	MSE	SDR
IWGPR(A to B)	0.78	2.40	0.69	3.44	0.60	4.63	0.44	6.14	0.32	8.27	0.24	9.65	0.16	10.8	0.12	10.94
BDA(A to B)	**0.63**	**3.34**	**0.48**	**4.40**	**0.40**	**5.78**	**0.34**	**7.60**	**0.25**	**9.01**	**0.14**	**10.3**	**0.06**	**11.0**	**0.08**	**11.8**
GPR (B)	0.96	1.49	0.79	2.52	0.66	4.17	0.61	5.01	0.52	7.39	0.42	8.14	0.36	8.20	0.25	9.18
IWGPR(B to A)	0.72	2.65	0.62	3.54	0.51	5.24	0.40	7.08	0.31	8.67	0.20	**10.3**	0.14	10.7	0.09	10.8
BDA(B to A)	**0.67**	**3.42**	**0.57**	**4.58**	**0.46**	**6.03**	**0.38**	**7.68**	**0.27**	**9.17**	**0.17**	10.1	**0.08**	**10.9**	**0.07**	**11.4**
GPR(A)	0.97	2.32	0.83	3.17	0.66	3.82	0.54	4.05	0.40	6.17	0.27	8.25	0.17	7.87	0.12	10.3

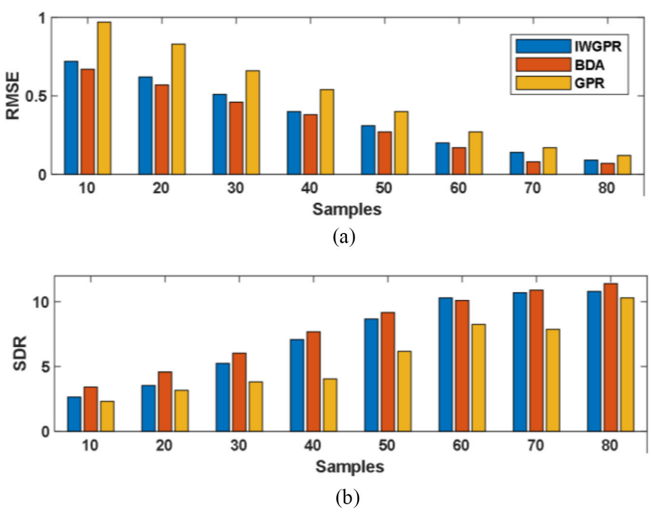


Fig. 17. Comparative results for MSE and SDR in the urban scenario (Experiment IV).

decrease from 0.18 to 0.13 deg^2 gradually. It indicates that TL-based method IWGPR can successfully model TL between different drivers. As for the comparative result of SDR, IWGPR obtains higher results than general GPR in different conditions, which shows the stability of IWGPR in prediction.

The qualitative analysis above demonstrates the advantage and performance of proposed method by comparing to general GPR (without TL). As for the comparison between different transferable driver behavior modelling methods, the performance of BDA is detailed in Fig. 17. With different number of target samples, the performance of BDA is slightly better than IWGPR in SDR and MSE, which demonstrates the conditional distribution improve the performance, while IWGPR only considers to adapt the marginal distribution.

V. CONCLUSION AND FUTURE WORK

In this paper, in order to solve the problem of knowledge transfer for driver behaviour modelling, an IW-based TL method, IWGPR, is proposed. Based on importance weight (IW), the proposed method is capable of using data collected from source driver to model the target driver and transfer the knowledge between two drivers. To estimate IW between different drivers efficiently, optimisation-based estimator, ULSIF is applied in the proposed method. After the estimation of IW, an importance weighted model selection (IWMS) method is developed to choose optimal parameters for IWGPR and improve the accuracy of model. Because of the ability of TL, IWGPR can significantly improve the performance of general GPR.

To test the proposed algorithm, four experiments are conducted. The toy regression example in Experiment I illustrates basic characteristics and mechanism of IWGPR. In Experiment II, with data of three drivers collected from a driving simulator, the proposed IWGPR performs better than general GPR with a higher accuracy. In Experiment III, naturalistic driving data collected in the highway are used to verify the adaptability of IWGPR. Because of TL, IWGPR can adapt to different drivers effectively and improve the performance of model for drivers with insufficient data. In order to fully verify the performance of IWGPR, naturalistic driving data are collected in the urban scenario and applied in Experiment IV, which contain driver operations from vehicle CAN bus. The last experiment demonstrates the effect of IWGPR in the urban lane-changing scenario. The main possible application of proposed algorithm IWGPR is to online collect the new driver's driving data for the model training and generate the output for ADAS, which can be used as a reference value for the operation of new driver.

Besides the application in the lane change scenario, as a general method, IWGPR can also be extended to other scenarios. In our future work, scenarios with complicated traffic situations will be considered.

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