Situation Awareness for Driver-Centric Driving Style Adaptation

Johann Haselberger *, Bonifaz Stuhr *, Bernhard Schick , and Steffen Müller

***Abstract*—There is evidence that the driving style of an autonomous vehicle is important to increase the acceptance and trust of the passengers. The driving situation has been found to have a significant influence on human driving behavior. However, current driving style models only partially incorporate driving environment information, limiting the alignment between an agent and the given situation. Therefore, we propose a situation-aware driving style model based on different visual feature encoders pretrained on fleet data, as well as driving behavior predictors, which are adapted to the driving style of a specific driver. Our experiments show that the proposed method outperforms static driving styles significantly and forms plausible situation clusters. Furthermore, we found that feature encoders pretrained on our dataset lead to more precise driving behavior modeling. In contrast, feature encoders pretrained supervised and unsupervised on different data sources lead to more specific situation clusters, which can be utilized to constrain and control the driving style adaptation for specific situations. Moreover, in a real-world setting, where driving style adaptation is happening iteratively, we found the MLP-based behavior predictors achieve good performance initially but suffer from catastrophic forgetting. In contrast, behavior predictors based on situation-dependent statistics can learn iteratively from continuous data streams by design. Overall, our experiments show that important information for driving behavior prediction is contained within the visual feature encoder. The dataset is publicly available at huggingface.co/datasets/jHaselberger/SADC-Situation-Awareness-for-Driver-Centric-Driving-Style-Adaptation.**

***Index Terms*—Driving style adaptation, situation awareness, clustering, unsupervised learning, artificial intelligence, intelligent vehicles.**

I. Introduction

As autonomous vehicle development advances, attention is shifting from technical realizability to achieving driving characteristics that are both comfortable and acceptable [1]. A crucial aspect of perceived driving comfort is influenced by the driving style, playing a vital role in fostering trust and acceptance of autonomous vehicles [2]–[5]. Considerable evidence shows that a driving style adaptation towards the human driver could improve the acceptance of autonomous driving functions and mitigate uncertainties associated with their usage [6]–[21]. The term "driving style" lacks a comprehensive and standardized definition [22]–[24]; however, definitions commonly agree that driving style encompasses a collection of driving habits developed and refined by a driver [25]–[29]. It is argued that drivers prefer a style similar to their own [30]–[37]. Current driver models or driving functions, however, depict an average driver with static parameters [23], [30], [38], lacking adaptation to individual drivers [19], [39]–[41]. While methods in the field of driving style adaptation primarily focus on ego-vehicle-dependent signals like acceleration and jerk values [42]–[47], the incorporation of the entire driving situation remains elusive. However, the driving situation has been found to have a significant influence on driving behavior [24], [48]–[54]. Furthermore, an alignment between an agent's capability and the given situation increases trust [55], [56]. Moreover, individuals' responses to different driving contexts constitute a significant aspect of driving style [10]. Therefore, we propose a situation-aware method to adapt the driving style to the specific human driver. To fully incorporate the driving situation, we utilize visual feature encoders to learn a representation of the environment. Building upon this representation, we propose and evaluate two distinct driving style models capable of learning a mapping from the driving situation to the driving behavior, mimicking the specific driver. Our contributions can be summarized as follows:

1) A situation-aware driving style adaptation method utilizing learned representations of the driving environment.

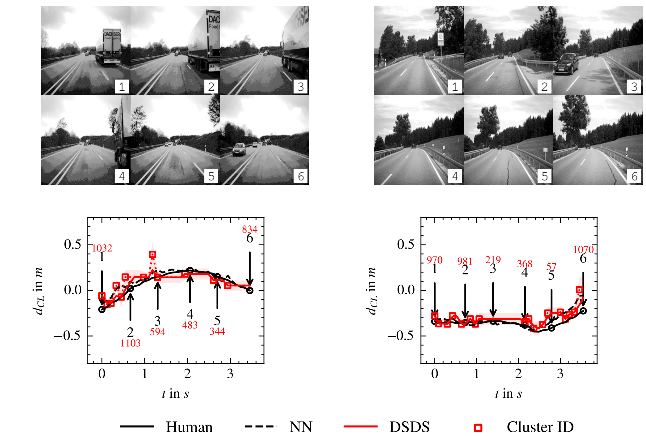

Fig. 1. Distance to lane center predictions of our proposed neural-network-based driving style model (NN) and the driving situation clustering approach (DSC) for two specific scenarios. The top row shows images of the driving situation in chronological order, and the bottom row shows the predicted trajectories and the recorded human behavior. Red squares denote a change in the situation cluster identified by the DSC approach. Corresponding images and their respective cluster IDs are annotated with arrows.

Manuscript received March 17, 2024. *(*contributed equally to this work.)*
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2) An interpretable clustering-based approach for learning situation-dependent driving behaviors and to constrain and control the driving style adaptation for specific situations.
3) A publicly accessible dataset including 1.8 million images and labeled driving behavior data of multiple drivers.
4) The Entropy-based Cluster Specificity (ECS) metric which uses proxy labels to measure the specificity of the found situation clusters.
5) The evaluation of unsupervised foundation models (DINOv2) and visual feature encoders pretrained supervised on ImageNet1K for driving style modeling and situation clustering.
6) The evaluation of MLPs and situation-dependent statistics for driving style modeling and their iterative training capabilities.

II. Related Work

In this section, we present an overview of related work in the field of driving style recognition and modeling, highlighting the employed input quantities, the derived output quantities, and the utilized modeling techniques.

Driving Style Input Quantities

For driving style modeling, the majority of approaches exclusively rely on vehicle BUS time-series data, incorporating information such as acceleration, jerk, and steering wheel angle [42]–[47]. When assessing the driving style solely based on ego-vehicle-centric features, the influence of the driving context is not considered. However, in various traffic scenarios the driving context either facilitates or constrains decision-making [27]. There is considerable evidence affirming that external conditions significantly influence driving behavior [24], [48]–[54]. Although weather has been shown to influence driving behavior significantly [57]–[60], the extent of this variation among individual drivers differs [61]. In addition to the influence of weather conditions, traffic also plays a pivotal role, especially when drivers encounter oncoming traffic, leading to deviations from the lane center [36], [62]–[67]. To incorporate the external context into the driving style analysis, previous works often rely on the isolated inclusion of weather information [68]–[71], road features [68]–[75], and traffic data [71], [73], [74], [76]–[78]. Frequently, the relationship with surrounding traffic is extracted from object lists of the vehicle's internal environment perception, as shown in [77]–[84]. In contrast, we utilize raw images from a front-facing camera to fully capture the driving situation without restricting the environment's representation to specific features or scenarios.

Driving Style Output Quantities

When examining the output quantities, it is evident that the majority of prior methods derive discrete driving style classes [43]–[45], [85], [86]. While categorizing into broad classes like defensive, moderate, or aggressive provides a high degree of interpretability, defining these classes and their boundaries remains highly subjective. In contrast, objective model outputs in the form of driving behavior indicators provide an alternative approach [82], [84], [87]–[90]. In addition to these dynamics-oriented indicators, the model parameters of classical mathematical driving behavior models are also predicted [82], [91]–[93]. Moreover, scores, such as sportiness or aggressiveness, are derived using predefined calculation procedures [44], [87], [94], [95]. In contrast to the broader driving style classes, the objective indicators of driving behavior offer the advantage of being directly integrable into the personalization of driver assistance systems or automated driving functions through constraints or target variables. Therefore, we use objective indicators of driving behavior in this work.

Driving Style Modeling Approaches

On the one hand, driving style modeling often relies on relatively simple rules based on behavioral patterns [94], [96]–[99] or statistical models [81], [91], [95], [100], [101]. On the other hand, more complex machine-learning-based methods are employed. This entails utilizing Support Vector Machines (SVMs) [102]–[105], K-Nearest Neighbors (KNN) [102], [103], [106] or Multilayer Perceptrons (MLPs) [102], [107]–[109] for driving style classification. Beyond the scope of pure classification, learning-based methods are also applied to learn a driving style and behavior representation [79], [110] or to predict specific driving-style-related scores [87]. To capture the temporal aspects of driving behavior and the corresponding driving situation, Recurrent Neural Networks (RNNs) are utilized [45], [47], [79], [83], [107], [111]. Even without utilizing images from a vehicle-mounted camera, Convolutional Neural Networks (CNNs) are often employed for driving style modeling [74], [83], [86], [108], [111], [112]. For converting time-series data of driving measurements into an image-like representation, so-called Driving Operational Pictures (DOPs) are used [47], [86], [113], [114].

In addition to the frequently utilized supervised approaches for driving style classification or behavior prediction, unsupervised clustering methods are also employed to identify groups of behaviors. These methods cluster data based on driving behavior metrics such as velocity, accelerations, jerk, or headway values [43], [80], [82], [85], [115], [116], or derived representations like risk levels or DOPs embeddings [104], [117]. This driving behavior clustering is commonly coupled with a preceding reduction of input dimensionality using manifold learning techniques [80], [117], [118]. In contrast, our approach does not rely on clustering behavior data but focuses on clustering the underlying environment representation derived from camera images to model the drivers' individual driving styles in a situation-specific manner.

III. Datasets

To assess driving style modeling capabilities of our proposed method, a large dataset with a high scenario diversity is needed to evaluate the situation behavior mapping. This dataset contains a wide range of situations for pretraining our method and can be considered as fleet data from a manufacturer.

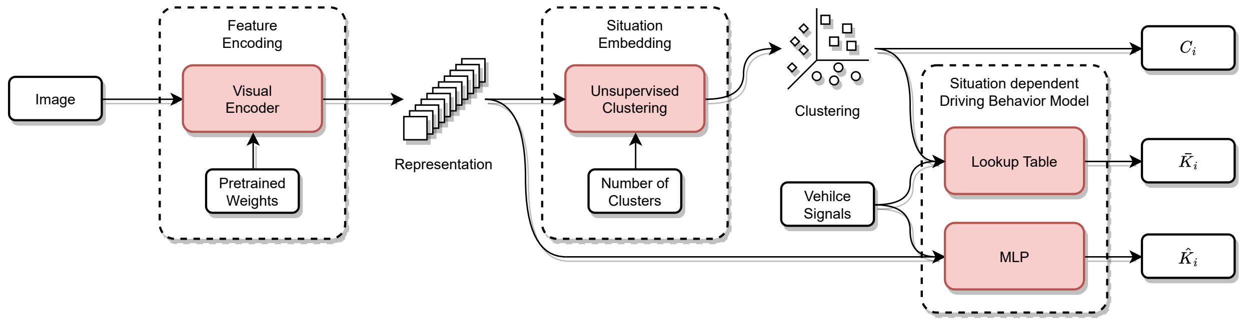

Fig. 2. High-level overview of the proposed method. Our method consists of a visual feature encoder that infers a representation from an image of a driving situation. This encoder is either pretrained on our pretrain dataset, pretrained on ImageNet1K, or a pretrained unsupervised (foundation) model. Utilizing this representation, unsupervised clustering is employed to associate each driving situation with a cluster C_i. This clustering can be used to identify and mask specific driving situations to constrain and control the driving style adaptation. We predict the target driving behaviors either with a statistical lookup table that uses the situation cluster C_i for indexing or with MLPs that use the representations from the visual encoder for situation awareness.

We denote this dataset as the pretrain dataset $\mathcal{D}_P$. For a fair evaluation of the adaptation capabilities of our method to various drivers and driving situations, data from multiple drivers obtained within similar environmental conditions is needed. These data represent the behavioral examples of a specific driver collected and used for driving style adaptation in the vehicle. This dataset is referred to as the validation dataset $\mathcal{D}_V$.

Data Collection

Since there is a lack of publicly accessible driving datasets covering both image data and driving behavior indicators, as recently discussed in [119], we collected over 16 hours of driving data from a single test driver using the JUPITER platform [120] as pretrain data. The data was captured over several months, ensuring a diverse range of road, traffic, and weather conditions.

For the validation data, we utilize the collected driving data from a previously conducted driving style subject study [119] using the same research vehicle as for the pretrain data collection. Within this study, the driving style of 62 subjects was subjectively and objectively analyzed while driving on a given route featuring city, rural, federal, and highway roads. The data was captured over a small period (two months), ensuring seasonal consistency for the different drivers. Out of this driver population, we randomly sample five drivers and enrich the dataset with the corresponding captured camera frames.

Dataset Preperation

To ensure a significant variation of driving situations in the camera stream, the original frame rate of $36\,\mathrm{Hz}$ is down-sampled to $10\,\mathrm{Hz}$. Sampling frames randomly to create the training and validation splits likely results in similar driving situations featured in both sets. To mitigate an overly optimistic evaluation of the generalization ability, we divide the entire driving dataset into equal time segments of three seconds each. Following this, the segments are randomly assigned to either the training or validation split of $\mathcal{D}_P$ and $\mathcal{D}_V$. We use $20\,\%$ of the samples for validation. To blur vehicle license plates and human faces in the camera frames, we utilize EgoBlur [121]. Furthermore, all subject-related data, including the socio-demographics, are anonymized.

Dataset

The final dataset is composed as follows: the pretrain set $\mathcal{D}_P$ is split into a training subset $\mathcal{D}_{P,T}$ with $242\,887$ samples, and a validation subset $\mathcal{D}_{P,V}$ with $61\,400$ samples. Similarly, the validation set $\mathcal{D}_V$ is split into a training subset $\mathcal{D}_{V,T}$ and a validation subset $\mathcal{D}_{V,V}$ with $138\,572$ and $34\,767$ samples. Each subset consists of 1280×960 images, driving behavior indicators like the distance to the lane center or longitudinal headway distances, vehicle signals like velocity or accelerations, as well as traffic conditions and road type labels. The entire unfiltered pretrain data and the unfiltered validation data of the five drivers (1.8 million samples), as well as the processed datasets, are publicly available at **huggingface.co/datasets/jHaselberger/SADC-Situation-Awareness-for-Driver-Centric-Driving-Style-Adaptation** under the CC BY 4.0 DEED license.

IV. Method

Our proposed method consists of three components: visual feature encoding, situation embedding, and situation-dependent driving behavior modeling. A graphical overview is provided in Figure 2. Without the loss of generalization, we select the distance to the center lane (d_{CL}) as the target variable to characterize the lateral driving style. Previous studies show that this quantity is highly driver-heterogenous and can be integrated into the development and evaluation of lateral driving functions [119], [122]–[124].

Visual Feature Encoding

To get a representation R_i of a given driving situation S_i, we pretrain a visual feature encoder $E(S_i)$ on our pretrain dataset $\mathcal{D}_{P,T}$. As the loss function $\mathcal{L}$, we calculate the mean squared error (MSE) between the predicted ($\hat{d}_{\mathrm{CL}}$) and the measured distance to the center lane of the human driver (d_{CL}) for the given situation:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}(d_{\mathrm{CL}} - \hat{d}_{\mathrm{CL}})^2 \tag{1}$$

Furthermore, we experiment with visual feature encoders pretrained supervised on ImageNet1K [125] and unsupervised on curated data to evaluate the performance of behavior prediction and situation clustering based on representations obtained from off-the-shelf encoders.

Situation Embedding

Given the multitude of diverse road, weather, and traffic situations encountered in real-world driving, the underlying situation space is not easily definable and manageable using traditional rule-based approaches. Therefore, we employ unsupervised clustering to associate each driving situation S_i with a cluster C_i utilizing the representation $R_i = E(S_i)$. In this way, we model the drivers' individual driving styles in a situation-specific manner without prior knowledge of the situation space. Moreover, besides a low computation effort, clustering provides high interpretability. The identified clusters can be examined utilizing the given mapping from the situation embeddings to the camera images and the corresponding vehicle signals. In this work, we use different variants of k-means clustering with the target number of clusters N_C as an adjustable parameter to regulate the situation-specificness for driving style adaption.

Situation Aware Driving Behavior

Using the assigned situation cluster C_i, we predict the target driving behavior indicators K_i with a statistical lookup table. To train each of the N_C entries of the lookup table, we gather objective driving behavior samples for each assigned situation embedding and calculate the target behavior indicators $\bar{K}_i$ based on derived statistics of the $N_{C_i}^{d_{\mathrm{CL}}}$ collected driving samples d_{CL}:

$$\bar{K}_i = \frac{1}{N_{C_i}^{d_{\mathrm{CL}}}} \sum_{j=1}^{N_{C_i}^{d_{\mathrm{CL}}}} d_{\mathrm{CL},j} \tag{2}$$

Based on the possible large amount of different situation clusters N_C, this is an efficient statistic-based method to predict the driving behavior indicators.

To further compare our cluster-based approach, we also train driving behavior models end-to-end directly on the situation images $\hat{K}_i = H(E(S_i))$, where H refers to fully-connected layers to obtain the final prediction $\hat{K}_i$. For a direct comparison to situation-dependent driving behavior modeling, we use the same visual feature encoder architectures. In contrast to the cluster-based approach that explicitly decouples the driving situation and the behavior modeling, the end-to-end approach only implicitly considers the driving situation, which reduces interpretability. From the perspective of a manufacturer, explicit situation-behavior mapping provides the possibility to constrain and control the driving style adaptation for specific situations.

Driver-Centric Driving Style Adaptation

Given substantial evidence that every driver has their unique driving style [13], [29], [48], [126]–[129], we adapt our model towards the driving style of specific drivers. Therefore, we freeze the visual feature encoder and the clusters learned on the pretrain dataset $\mathcal{D}_{P,T}$. Only the entries of the situation-dependent lookup table are updated using the driver-specific behavior data $\mathcal{D}_{V,T}$. As a second approach, we train fully-connected predictor heads on the representations of the frozen visual feature encoder for each specific driver separately. Separating the training of the visual encoder and clustering from behavior modeling allows training these two components on a wide variety of situations obtained from fleet data not necessarily encountered by a single driver. Furthermore, this split enables the training of time, data, and resource-consuming feature encoders by the manufacturer on dedicated computation machines rather than on the actual vehicles. Similarly, the pretraining of the clusters provides the possibility to share a common situation-behavior-mapping across all vehicles, facilitating consistency and testability from the manufacturer's perspective. On top of this, clustering can mitigate the effects of catastrophic forgetting when adapting to new situations. The driver-centric training of the situation-dependent lookup table and fully-connected heads can be done directly on the vehicle.

Integration into ADAS / HAF

Compared to direct control quantities like steering angle or gas pedal position, the derived driving behavior indicators from our model can be treated as constraints or target values for low-level controllers like in [78], [82], [100], [130]. Decoupling driving behavior indicators from the actual control quantities ensures a driving style adaptation safeguarded by the low-level controller. Moreover, our method is not restricted to lateral indicators such as the distance to the lane center and, in theory, can be generalized to other use cases, such as adapting longitudinal headway distances for Adaptive Cruise Control (ACC). Besides using the clustering as indexing for the driving behavior lookup table, the situation embeddings can also be seen as additional output of our method. This output can be further used to mask specific situations for other driving behavior models, like the MLPs used in this work. Decoupling situation clustering from driving behavior modeling provides the possibility of employing various types of visual feature encoders for both tasks.

V. Experiments

We conduct various experiments to evaluate our method regarding its capabilities to model the human situation-aware driving behavior, its adaptability to different drivers, and the specificity of the identified situation clusters. For all experiments, we report mean and standard deviations across five runs.

Metrics

For evaluation of the lateral driving behavior modeling, we utilize the root-mean-square error (RMSE) between the human and the predicted distance to the lane center $\hat{d}_{\mathrm{CL}}$:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (d_{\mathrm{CL}} - \hat{d}_{\mathrm{CL}})^2} \tag{3}$$

For assessing the adaptation performance on the validation subset $\mathcal{D}_{V,V}$, we average the error across all five drivers. We report RMSE values for the entire validation datasets $\mathcal{D}_{P,V}$ and $\mathcal{D}_{V,V}$ (All) and on subsets containing only rural situations (Rural Only). As additional benchmarks, we refer to the curve-cutting-gradient-based driving styles from [123] without considering the driving situation. These static driving styles consist of constant lane centering (Rail), minimal curve cutting (Passive), and a sportive driving style with high curve cutting gradients (Sportive). The statistical significance of the mean differences between our proposed method and the static driving styles was analyzed using jamovi [131], an open-source statistical software.

To quantitatively evaluate the clustering of the representations into specific situations, we propose the Entropy-based Cluster Specificity (ECS) metric. As the underlying situation space is unknown and cannot be clearly described, our metric incorporates N_L discrete labels, which act as proxy labels for the driving situation. In our case, we define six proxy labels: road type, curvature, as well as type and distance of oncoming and leading vehicles. Thereby, the l-th label is binned into N_{B_l} bins. Using the learned mapping of the driving situation to the c-th cluster centroid, we can select a subset L_c of all label data L. For each label $L_{c,l}$ in the selected subset, we utilize the normalized Shannon entropy [132]:

$$h(L_{c,l}) = -\frac{\sum_{i=1}^{N_{B_l}} p(L_{c,l,i}) \log p(L_{c,l,i})}{\log(N_{B_l})} \tag{4}$$

to define the specificity value $s(L_{c,l}) = 1 - h(L_{c,l})$. We employ the inverse of the entropy as we want to identify highly specialized clusters. We then combine the centroid-wise maximum and average specificity values:

$$\mathrm{ECS} = \frac{1}{N_C}\sum_{c=1}^{N_C}\left(\max_{l\in N_L} s(L_{c,l}) \times \frac{1}{N_L}\sum_{l=1}^{N_L} s(L_{c,l})\right) \tag{5}$$

We balance contributions from highly specialized centroids by taking the maximum and contributions from centroids specialized across multiple labels by calculating the average over all N_L labels. For the final ECS score, we calculate the average across all clusters N_C. The ECS metric is bound between 0 and 1, as it is derived from the normalized Shannon entropy.

Models

For our visual feature encoder, we experiment with the convolution-based ResNet-18 [133], ResNet-50 [133], ResNeXt-50 [134] models, and a large attention-based visual image transformer (ViT-L) [135]. We either pretrain these models on our dataset or use their pretrained versions on ImageNet1K [125]. As an unsupervised foundation model for the visual feature encoder, we select DINOv2 with registers [136] in the sizes small (DINO-S), big (DINO-B), large (DINO-L), and giant (DINO-G). All DINOv2 models are based on visual image transformers. Visual, unsupervised foundation models like Dinov2 are intended to learn representations that can directly be used for any image-level or pixel-level task. For clustering of the representations, we utilize classical and spherical unsupervised K-Means Clustering [137], [138]. As predictor heads for the driving behavior based on the representations, we experiment with fully-connected linear layers and MLPs.

Implementation Details

We implement all methods in PyTorch 2.1.1 and train them on a single machine with up to eight NVIDIA A100 GPUs. For GPU accelerated training of both K-Means variants, we utilize the Faiss library [138]. For training of the feature encoders, we resize the input images to height 224, crop 224×224 patches with center cropping, apply AugMix augmentations [139] on the images, and normalize them with mean 0.5 and standard deviation 0.5. We use AdamW [140] with standard parameters as optimizer, a cosine annealing learning rate schedule, a batch size of 256, and tune learning rates as well as epochs separately for each model. For the supervised pretrained models, we utilize the weights provided by torchvision 0.16.1 [141]. Since there are different versions of ImageNet1K weights, we choose the weights with the best reported performance on ImageNet1K. We follow the original implementation of Dinov2 and use the provided weights [136] to infer representations of our dataset. All MLP heads consist of three layers with $[2048, 2048, 1]$ units, ReLU activations, batch normalization [142], and a tanh output activation. Before further processing by K-Means clustering or the fully-connected heads, we standardize the representations by removing the mean and scaling to unit variance. Our implementation is publicly available at **github.com/jHaselberger/SADC-Situation-Awareness-for-Driver-Centric-Driving-Style-Adaptation**.

Situation Aware Driving Behavior

To test the capabilities of our models to predict the human situation-aware driving behavior, we train neural-network-based (NN) behavior predictors end-to-end on the pretrain dataset $\mathcal{D}_{P,T}$ and report the RMSE results on $\mathcal{D}_{P,V}$ in Table I. We use the best-performing feature encoders of the end-to-end training for driving situation clustering (DSC). For training the driving situation dependent statistics (DSDS), the number of clusters N_C is varied from 5 to 3000 and the best-performing configuration is reported. Compared to the static driving styles, both NN and DSC predict human driving behavior with significantly ($p < .001$) lower mean errors according to the Post-hoc test of a robust analysis of variance (ANOVA) ($F(2.0, 48990) = 15814,\ p < .001$). Overall, the end-to-end trained models lead to the lowest RMSE values for both domains. However, the DSC approach leads to more stable results, indicated by the lower standard deviations. For the end-to-end method, ResNet-18 performes the best in our experiments with an RMSE value of 0.0806 ± 0.0014. However, as we observe in the results of the DSC method, the larger representation sizes of the ResNet-50 and ResNeXt-50 encoders lead to performance improvements when the behavior prediction is decoupled from training the feature encoder. Furthermore, it can be seen that the classical K-Means variant leads to better results compared to the spherical counterpart. It

TABLE I
RESULTS OF OUR METHODS ON $\mathcal{D}_{P,V}$ WITH VISUAL FEATURE ENCODERS PRETRAINED ON $\mathcal{D}_{P,T}$.

	Visual Encoder	Behavior Predictor	All RMSE	Rural Only RMSE
NN	ResNet-18	MLP	**0.0806 ± 0.0014**	**0.0923 ± 0.0022**
	ResNet-50	MLP	0.0822 ± 0.0013	0.0978 ± 0.0013
	ResNeXt-50	MLP	0.0823 ± 0.0013	0.0984 ± 0.0019
DSC	ResNet-18	DSDS-KM	0.1075 ± 0.0001	0.1080 ± 0.0003
		DSDS-KMS	0.1159 ± 0.0005	0.1170 ± 0.0004
	ResNet-50	DSDS-KM	0.1035 ± 0.0005	0.1314 ± 0.0005
		DSDS-KMS	0.1093 ± 0.0004	0.1332 ± 0.0004
	ResNext-50	DSDS-KM	0.1023 ± 0.0008	0.1272 ± 0.0009
		DSDS-KMS	0.1077 ± 0.0007	0.1308 ± 0.0005
Static		Passive	0.2519	0.2115
		Rail	0.2314	0.2027
		Sportive	0.2801	0.2460

TABLE II
RESULTS OF OUR METHODS ON $\mathcal{D}_{V,V}$ WITH VISUAL FEATURE ENCODERS PRETRAINED ON $\mathcal{D}_{P,T}$ AND PREDICTION HEADS TRAINED ON $\mathcal{D}_{V,T}$.

	Visual Encoder	Behavior Predictor	All RMSE	Rural RMSE
NN	ResNet-18	MLP	0.0737 ± 0.0010	0.0752 ± 0.0021
		Linear	0.1750 ± 0.0048	0.1809 ± 0.0083
	ResNet-50	MLP	0.0685 ± 0.0012	0.0755 ± 0.0009
		Linear	0.1570 ± 0.0028	0.1506 ± 0.0040
	ResNeXt-50	MLP	**0.0677 ± 0.0010**	**0.0739 ± 0.0014**
		Linear	0.1566 ± 0.0036	0.1551 ± 0.0034
DSC	ResNet-18	DSDS-KM	0.1027 ± 0.0005	0.0954 ± 0.0009
		DSDS-KMS	0.1115 ± 0.0009	0.1086 ± 0.0009
	ResNet-50	DSDS-KM	0.1026 ± 0.0011	0.1084 ± 0.0013
		DSDS-KMS	0.1087 ± 0.0011	0.1096 ± 0.0011
	ResNext-50	DSDS-KM	0.1006 ± 0.0004	0.1149 ± 0.0009
		DSDS-KMS	0.1053 ± 0.0007	0.1158 ± 0.0013
Static		Passive	0.2653	0.2383
		Rail	0.2716	0.2453
		Sportive	0.2738	0.2470

is evident that, unlike static driving style models, our learning-based methods deliver slightly better results in all situations compared to the rural subset. On the one side, this may be attributed to the higher amount of available training data. On the other side, the rural-only subset consists of a higher behavior variability, given the higher variance in curve radii.

Driver-Centric Driving Style Adaptation

Since the previous experiment demonstrates the general modeling capabilities of our method, we further investigate the adaptability to different drivers. Therefore, we freeze the feature encoders and the situation clustering pretrained on $\mathcal{D}_{P,T}$ and train the predictor heads for each driver in the dataset $\mathcal{D}_{V,T}$ separately. As shown in Table II and by the Post-hoc tests of a robust ANOVA $(F(2.0, 5755) = 2650,\ p < .001)$, the learning-based methods outperform the static driving styles significantly with $p < .001$. For the RMSE metric, the MLP behavior predictor performs the best, followed by DSDS and the linear model. Similar to the pretrain experiments, DSDS turned out to be the most stable model. As indicated by the DSC results in Table I, a larger representation size positively impacts performance in most cases when the predictor heads for the different drivers are trained separately from the visual feature encoder. Moreover, the lower RMSE values on $\mathcal{D}_{V,V}$ compared to $\mathcal{D}_{P,V}$ show that the feature encoders pretrained on $\mathcal{D}_{P,T}$ provide beneficial representations for situation-dependent driving behavior modeling of different drivers. This can also be seen in the reduced performance gap between the two domains. These results support the underlying concept of our adaptation method to decouple training of the visual feature encoder from behavior prediction. This enables the incorporation of a wide variety of situations obtained from fleet data and to share a common situation behavior mapping.

Impact of Clusters Quantity

To study the impact of the number of clusters, we vary the cluster quantity N_C from 5 up to 3000 while keeping the remaining behavior modeling the same. As shown in Figure 3 a), a decreasing trend in the resulting RMSE values can be observed during training across all drivers. However, for a higher number of clusters, the validation curve shows convergence or slight overfitting behavior. This confirms the dependency of the driving behavior modeling accuracy concerning N_C. As shown in Figure 3 b) and c), a lower number of clusters results in a coarser estimate of the driving behavior while maintaining the general trend in curve cutting. This can be attributed to the higher number of driving samples assigned to the same situation cluster, which are taken into account for the statistic-based driving style modeling. Increasing the number of clusters up to the optimum leads to a higher level of specialization of the learned clusters and a more situation-dependent capture of the human driving behavior, resulting in a more accurate reproduction of the human driving style.

Impact of Pretrained Visual Feature Encoders

To quantify if a pretraining on a task-specific pretrain dataset is necessary, we infer representations with models pretrained supervised on ImageNet1K and pretrained unsupervised on curated data from different sources. Pretrained models on publicly available datasets alleviate the time and resource requirements for gathering a large-scale driving dataset. Furthermore, for unsupervised learning, studies show beneficial characteristics of the learned representations, like the transferability to various target tasks [143]–[147] or the existence of more detailed information in the representation than supervised learning [148], [149]. Therefore, the representations of these models could have beneficial characteristics for situation-based clustering. As seen in Table III, the overall performance of supervised and unsupervised pretraining is very similar. This aligns with other studies [143]–[145], [147] that show evidence that unsupervised pretraining can be competitive with supervised pretraining without requiring labeled data. Additionally, no clear correlation is observed between the evaluated representation sizes and the resulting RMSE values. However, compared to the task-specific pretraining results summarized in Table II, we observe a notable drop in performance. This decrease in performance is similar for both the NN and DSC approaches, with DSC now only slightly outperforming the static

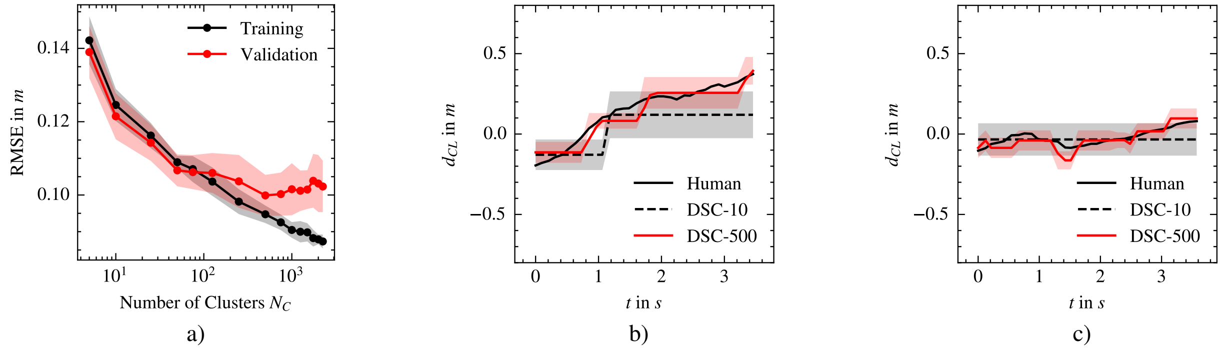

Fig. 3. a) Training and validation RMSE of the DSC method on $\mathcal{D}_{V,V}$ for an increasing number of clusters N_C utilizing the ResNeXt-50 feature encoder pretrained on $\mathcal{D}_{P,T}$. b) and c) Predictions of the DSC approach with ResNeXt-50 feature encoding for two specific driving situations with $N_C = 10$ (DSC-10) and $N_C = 500$ (DSC-500).

TABLE III

RESULTS OF OUR METHODS ON $\mathcal{D}_{V,V}$ WITH VISUAL FEATURE ENCODERS PRETRAINED SUPERVISED ON IMAGENET1K (IN) OR UNSUPERVISED ON CURRATED DATA (DINO) AND PREDICTION HEADS TRAINED ON $\mathcal{D}_{V,T}$.

	Visual Encoder	Behavior Predictor	All RMSE	Rural Only RMSE	Visual Encoder	Behavior Predictor	All RMSE	Rural Only RMSE
NN	ResNet18-IN	MLP	**0.1652 ± 0.0011**	**0.1554 ± 0.0008**	Dino-S	MLP	0.1658 ± 0.0007	0.1654 ± 0.0017
		Linear	0.3845 ± 0.0038	0.3043 ± 0.0013		Linear	0.4823 ± 0.0059	0.3255 ± 0.0038
	ResNet50-IN	MLP	0.1731 ± 0.0004	0.1614 ± 0.0008	Dino-B	MLP	0.1665 ± 0.0010	0.1610 ± 0.0017
		Linear	0.4513 ± 0.0013	0.2801 ± 0.0014		Linear	0.4903 ± 0.0034	0.3086 ± 0.0035
	ResNeXt50-IN	MLP	0.1732 ± 0.0008	0.1609 ± 0.0007	Dino-L	MLP	0.1684 ± 0.0005	0.1612 ± 0.0008
		Linear	0.4627 ± 0.0014	0.2700 ± 0.0012		Linear	0.4842 ± 0.0037	0.2946 ± 0.0077
	ViT-L-IN	MLP	0.1752 ± 0.0011	0.1721 ± 0.0011	Dino-G	MLP	**0.1653 ± 0.0001**	**0.1597 ± 0.0021**
		Linear	0.4118 ± 0.0077	0.3115 ± 0.0019		Linear	0.4849 ± 0.0048	0.2754 ± 0.0012
DSC	ResNet18-IN	DSDS-KM	0.2366 ± 0.0008	0.2151 ± 0.0014	Dino-S	DSDS-KM	0.2289 ± 0.0023	0.2102 ± 0.0048
		DSDS-KMS	0.2370 ± 0.0006	0.2166 ± 0.0009		DSDS-KMS	0.2301 ± 0.0010	0.2102 ± 0.0025
	ResNet50-IN	DSDS-KM	0.2384 ± 0.0006	0.2160 ± 0.0004	Dino-B	DSDS-KM	0.2261 ± 0.0017	0.2100 ± 0.0022
		DSDS-KMS	0.2390 ± 0.0002	0.2166 ± 0.0008		DSDS-KMS	0.2280 ± 0.0014	0.2111 ± 0.0044
	ResNeXt50-IN	DSDS-KM	0.2389 ± 0.0002	0.2161 ± 0.0004	Dino-L	DSDS-KM	0.2283 ± 0.0014	0.2104 ± 0.0011
		DSDS-KMS	0.2389 ± 0.0004	0.2171 ± 0.0010		DSDS-KMS	0.2290 ± 0.0009	0.2126 ± 0.0023
	ViT-L-IN	DSDS-KM	0.2382 ± 0.0003	0.2157 ± 0.0008	Dino-G	DSDS-KM	0.2258 ± 0.0015	0.2099 ± 0.0018
		DSDS-KMS	0.2381 ± 0.0002	0.2161 ± 0.0004		DSDS-KMS	0.2260 ± 0.0015	0.2108 ± 0.0018
Static		Passive	0.2653	0.2383		Passive	0.2653	0.2383
		Rail	0.2716	0.2453		Rail	0.2716	0.2453
		Sportive	0.2738	0.2470		Sportive	0.2738	0.2470

driving styles. According to robust ANOVAs, the mean differences of the errors remain statistically significant ($p < .001$) for both the visual feature encoders pretrained supervised on ImageNet1K ($F(2.0, 6507) = 685,\ p < .001$) and unsupervised on curated data ($F(2.0, 6155) = 1047,\ p < .001$). Although these pretrained feature encoders can lead to a more situation-specific clustering, as shown in Figure 4, the observed drop in performance can be attributed to unwanted invariances or missing information required for driving behavior prediction in the representations. One potential explanation for this can be drawn from the qualitative analysis of the situation cluster images, exemplarily shown in row four of Figure 4. Here it is indicated that the clusters trained on the representations obtained from the visual feature encoders pretrained on $\mathcal{D}_P$ are more sensitive to the road curvature. In contrast, the other visual feature encoders focus more on the general visual appearance of the scene. Overall, it is evident that all representations obtained from the different variants of feature encoders are able to form plausible situation clusters. However, there are possible shortcomings, such as unclear driving situations or over-specification, as highlighted in the last row of Figure 4.

Cluster Specificity

To quantitatively analyze the specificity of the found situation clusters, we utilize our proposed ECS metric for the clustered representations obtained from the different visual feature encoders. As seen in Figure 5 a), the visual feature encoders pretrained supervised on ImageNet1K and unsupervised on curated data achieve higher specificity compared to the visual feature encoders pretrained on our dataset $\mathcal{D}_{P,T}$. Generally, we observe increasing specificity values for an increasing number of clusters N_C and stable specificity results across multiple runs in our experiments. The unsupervised Dinov2 models lead to the highest specificity, even for a lower number of clusters. This high specificity is also visible in the cluster image samples of Figure 4, where the high ECS scores underline the ability to differentiate driving situations in detail. However, a higher specificity can lead to a decrease in generalization and does not generally correlate with a good performance on a target task like behavior prediction. This can be seen in the higher RMSE values of the Dinov2 models and the models pretrained on ImageNet1K. Therefore, archiving a high precision on the target task (generalization) while

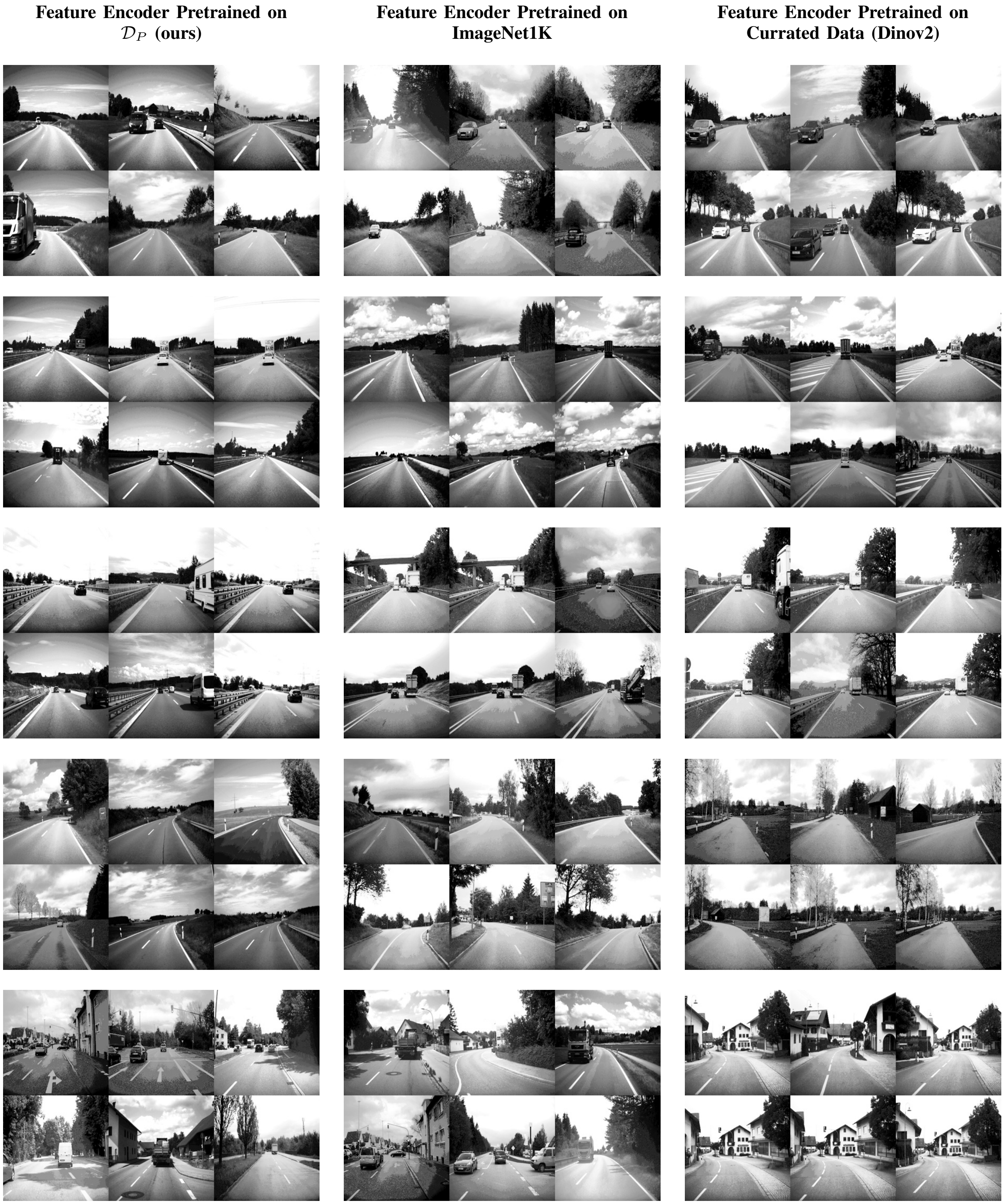

Fig. 4. Sample images of learned situation clusters using the representations from the visual feature encoders pretrained on our pretrain dataset $\mathcal{D}_{P,T}$, ImageNet1K, and in an unsupervised manner on curated data from different sources. For each situation cluster, we sample six images randomly from the set of assigned driving situations of $\mathcal{D}_{V,T}$. In the first four rows, we aim to highlight various aspects of potential driving situations, including oncoming traffic, following vehicles, overtaking, and driving on rural roads. In the last row, possible shortcomings of the clusters, such as unclear driving situations or over-specification, are shown.

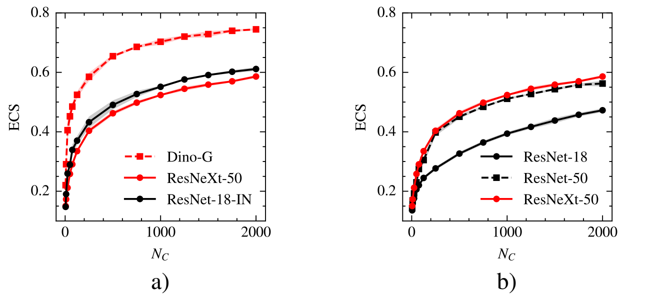

Fig. 5. a) Comparison of the Entropy-based Cluster Specificity (ECS) over the number of clusters N_C of the best-performing models for pretraining variant. b) ECS curves for the models pretrained on our pretrain dataset $\mathcal{D}_{P,T}$.

maintaining high specificity is beneficial for our method. In our experiments, such a trend can be observed for the visual feature encoders trained on our pretrain dataset, as shown in Figure 5 b), where higher-performing models also exhibit higher specificity.

Iterative Driving Style Adaptation

To evaluate the capability of our method to adapt to the driving style of a specific driver synchronously while gathering driving data, we split the dataset $\mathcal{D}_{V,T}$ into smaller subsets. We maintain the temporal order of the driving data when splitting into these subsets to mirror a real-world recording. For each training iteration, the models are trained on the respective subset until all driving data has been processed. We experiment with subsets that contain $10\,\%$, $1\,\%$, and $0.5\,\%$ of the training dataset $\mathcal{D}_{V,T}$. For each iteration, we validate our models using the entire validation set $\mathcal{D}_{V,V}$ to show overall improvements during the iterative training. The training curves, visualized in Figure 6, show that the DSC approach converges to the same RMSE as when trained on the entire dataset $\mathcal{D}_{V,T}$ at once. This behavior is expected since the lookup table training eliminates catastrophic forgetting by design, as the calculation of the statistics leads to the identical lookup table entries when training on the dataset iteratively or when training on the entire dataset $\mathcal{D}_{V,T}$. Furthermore, the lookup table approach is low in training time and memory consumption since only the number of assigned samples and their sum need to be saved for each situation cluster. In contrast, for the MLP-based driving behavior prediction, catastrophic forgetting can be observed. After the initial gains achieved by using the learned model from the previous iteration as initialization for the current iteration, no further increase in performance is visible. However, after seeing only a few training samples, the performance of the MLP increases significantly and is outperformed by the fully-trained lookup table only by a small margin. The MLP's capability to learn from a small number of samples and the performance variations among different pretrained feature encoders implies that the information embedded into the feature encoder significantly impacts the performance of behavior prediction.

VI. Conclusion

This work shows that a situation-aware prediction of human driving behavior based on camera images that capture the driving environment significantly surpasses the performance of several static driving styles. Moreover, a driving style adaptation based on visual feature encoders and situation clusters pretrained on fleet data results in a precise driving behavior modeling of different drivers with an average RMSE of $6.77\,\mathrm{cm}$. This shows that a setup with a visual feature encoder pretrained, e.g., by the manufacturer, and with decoupled driver-specific prediction heads, like MLP- and driving-situation-clustering-based models, is feasible. Furthermore, we experiment with visual feature encoders pretrained on other datasets to evaluate the need for dedicated task-specific pretraining datasets. The qualitative results show that the different visual feature encoders focus on different aspects of driving situations. To analyze these aspects quantitatively, we introduce an entropy-based cluster specificity metric. Using this metric, we observe that visual feature encoders pretrained on other datasets exhibit higher specificity values. It is important to note that cluster specificity does not necessarily correlate with performance, and overspecialization on unrelated aspects could negatively impact driving behavior prediction. However, a positive trend between higher specificity and a lower RMSE value for driving behaviour modeling can be observed for the visual feature encoders pretrained on our dataset. From a manufacturer's point of view, higher specificity values could prove advantageous in constraining and controlling driving style adaptation for specific situations with greater detail. Therefore, a two-branched version of our method with a branch for behavior prediction and a branch for situation masking could be realized with two different visual feature encoders. For an application-oriented test we evaluate the model's capability to be trained synchronously while gathering driving data. While the MLP-based behavior predictors achieve good performance initially, they suffer from catastrophic forgetting and are unable to learn from a continuous data stream. In contrast, the driving situation-dependent statistics can iteratively learn from the new driving samples by design. Overall, we found that the underlying visual feature encoder significantly impacts the performance of the driving behavior prediction, indicating that relevant information for driving behavior prediction is contained within situation-dependent representations.

Limitations

A potential limitation of our work is the usage of a single image for behavior prediction, which could be extended in future work into a sequence-based approach to incorporate the temporal information into the predictions. Our proposed publicly available dataset is already suitable for temporal methods. Furthermore, driving behavior predictors can be improved by utilizing more advanced models than MPLs or by improving the situation clustering and the statistical inference of the DSC approach. One interesting direction would be to train separate prediction heads per situation cluster. While our method can theoretically predict multiple driving behavior indicators, additional research needs to be conducted to explore other use cases, such as predicting longitudinal indicators suitable for Adaptive Cruise Control (ACC). Additionally, it is important to highlight that the collection of data for autonomous driving is

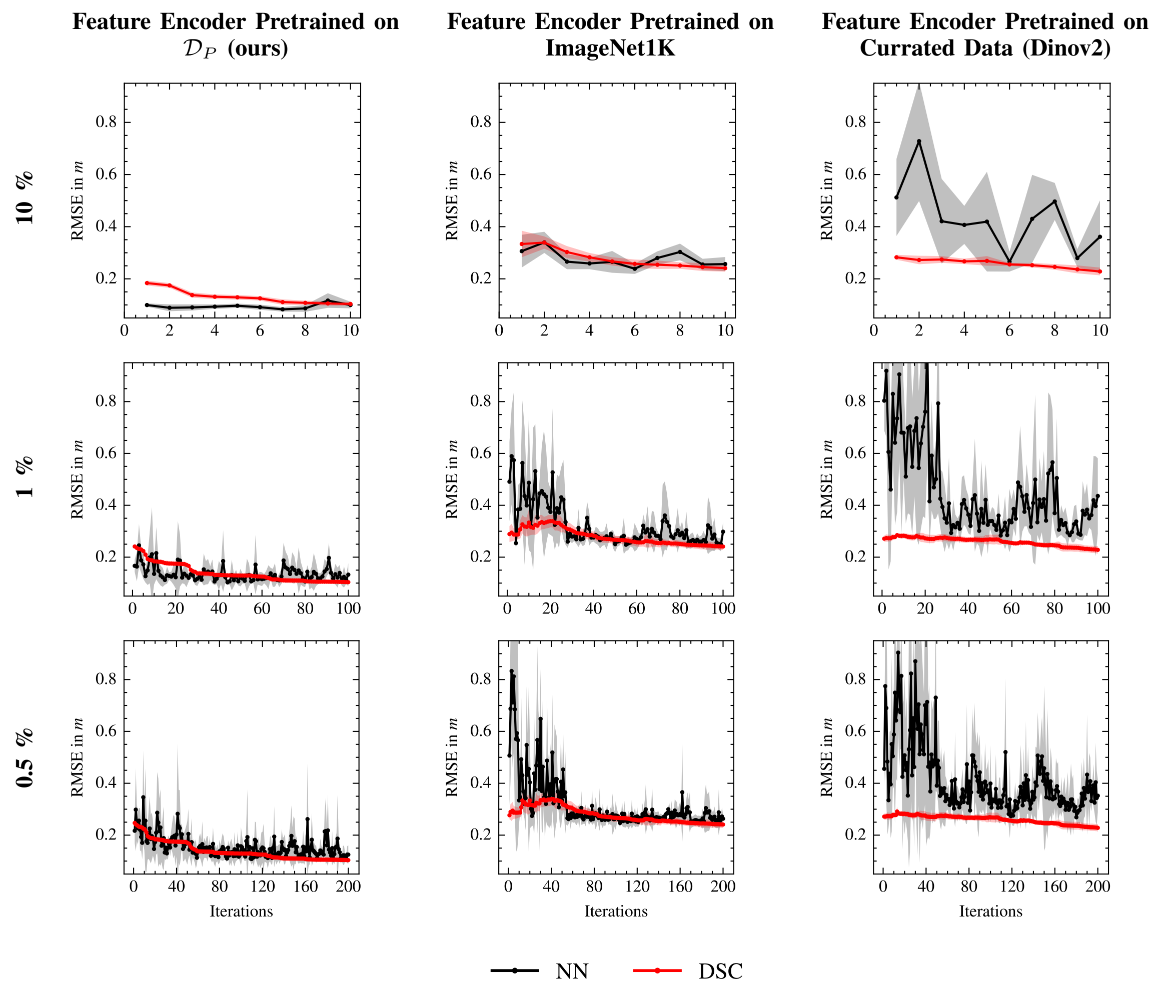

Fig. 6. Training curves for the NN and DSC-based driving behavior prediction when trained iteratively on subsets of $\mathcal{D}_{V,T}$. The subset sizes are $10\,\%$, $1\,\%$, and $0.5\,\%$ of the training data $\mathcal{D}_{V,T}$. The performance based on feature encoders pretrained on our pretrain dataset $\mathcal{D}_{P,T}$, ImageNet1K and in an unsupervised manner on curated data from different sources is shown.

an ongoing effort, and datasets like ours do not encompass all possible real-world driving scenarios that are crucial to ensure safe and practical deployment. Although the results show significant improvements compared to static driving styles, there is still a need for a more profound understanding of how sensitive human driving behavior is regarding variations in distances to the lane center.

Ethical and Responsible Use

Overall, our work contributes to the ongoing research in the field of autonomous driving, which still deals with unresolved ethical and legal questions. Our method intends to adapt behavior predictors to the driving style of different drivers live during driving. While a live adaptation should be treated with caution, we mitigate possible risks by decoupling driving behavior indicators from the actual control quantities. This enables a driving style adaptation safeguarded by the low-level controller. Furthermore, considering the limitations of our dataset, real-world tests should be conducted with care in a safe environment. To publish the data concerning privacy policies, we utilized a state-of-the-art anonymization framework to blur human faces and vehicle license plates to mitigate privacy concerns.

Acknowledgments

This work is being conducted as part of a research project of the Institute for Driver Assistance Systems and Connected Mobility (IFM) of the Allgäu Research Center at the University of Applied Sciences Kempten.

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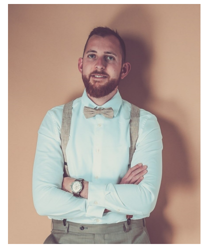

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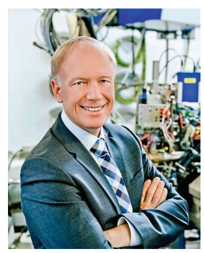

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