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Drivers’ Manoeuvre Prediction for Safe HRI

Erwin Jose Lopez Pulgarin¹

Guido Herrmann¹

Ute Leonards²

Abstract—Machines with high levels of autonomy such as robots and our growing need to interact with them creates challenges to ensure safe operation. The recent interest to create autonomous vehicles through the integration of control and decision-making systems makes such vehicles robots too. We therefore applied estimation and decision-making mechanisms currently investigated for human-robot interaction to human-vehicle interaction. In other words, we define the vehicle as an autonomous agent with which the human driver interacts, and focus on understanding the human intentions and decision-making processes. These are then integrated into the robot’s/vehicle’s own control and decision-making system not only to understand human behaviour while it occurs but to predict the next actions. To obtain knowledge about the human’s intentions, this work relies heavily on the use of motion tracking data (i.e. skeletal tracking, body posture) gathered from drivers whilst driving. We use a data-driven approach to both classify current driving manoeuvres and predict future manoeuvres, by using a fixed prediction window and augmenting a standard set of manoeuvres. Results are validated against drivers of different sizes, seat preferences and levels of driving expertise to evaluate the robustness of the methods; precision and recall metrics higher than 95% for manoeuvre classification and 90% for manoeuvre prediction with time-windows of up to 1.3 seconds are obtained. The idea of prediction adds a highly novel aspect to human-robot/human-vehicle interaction, allowing for decision and control at a later point.

I. INTRODUCTION

As the field of robotics expands and the definition of personal robots changes, more and more machines traditionally considered non-autonomous systems will become autonomous agents (i.e. robots). A Person Carrier Robot, as defined in standard ISO 13482:2014 [1], shares the same functionality as a semi-autonomous or autonomous vehicle. As robot bodies become more diverse, with faster, bigger and heavier moving parts, a safe operation in a seemingly interactive environment becomes a critical task.

Human-vehicle interaction (HVI) can therefore be seen as a subset of human-robot interaction (HRI) (Figure 1). General HRI considers a constant interaction between the agents and the environment simultaneously, in a potentially open world with a high level of uncertainty (i.e. non-structured environments and defined tasks). As HVI considers that the two agents (i.e. the human driver and the vehicle) share the same physical space, interaction between the human and the environment is mediated by the robot/vehicle; this reduces interaction between the human and the robot to a set of tasks

constrained by the physical space and the capabilities of the robot or vehicle. With this formulation, concepts and tools useful for HRI can be translated to HVI and vice-versa as long as well defined tasks are present (e.g. object handover task).

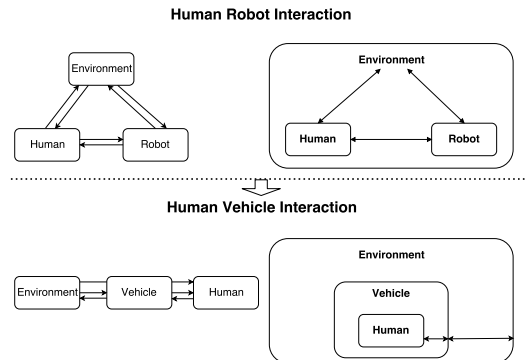


Fig. 1: Human-Robot interaction vs Human-Vehicle interaction

When two autonomous agents interact with each other, understanding the other agent’s intentions and decision-making process is crucial for seamless interaction, as happens naturally in human-human interaction according to the theory of mind [2].

Seminal work in human-robot-interaction has shown that continuous and dynamic analysis of human movements can be used successfully to predict future human actions in an on-line decision-making framework [3]. Encouraged by studies that showed that basic integration of driver information into a control framework (e.g. MPC) is feasible [4], we here apply a HRI strategy to an autonomous vehicle scenario. To the best of our knowledge, this is the first time that an online analysis and prediction of human movement intentions is integrated for vehicle systems, moving forward from earlier attempts in which either driving parameters such as driver behaviour [5] [6], driver intention recognition [7] or motion predictability alone [8] [9] were explored.

By bringing together concepts from HRI for behaviour prediction between agents with vehicle dynamics knowledge for task definition, an adaptable machine learning (data-driven) approach can be implemented in vehicles. As prediction is a crucial concept in decision-making, applying it to a vehicle scenario integrates the human and a (semi)-autonomous car. Hence, it can improve human-vehicle interaction and it can lead to better, more enjoyable and safe operation (e.g. vehicle adapting to driver/key passenger requirements about control handover, vehicle optimizing power train system).

¹E. Lopez and G. Herrmann are with the School of Civil, Aerospace and Mechanical Engineering (CAME), University of Bristol, Bristol, UK erwin.lopez@bristol.ac.uk and g.herrmann@bristol.ac.uk

²U. Leonards is with the School of Experimental Psychology, University of Bristol, Bristol, UK ute.leonards@bristol.ac.uk

The main contributions of this work are twofold: firstly, we replicate, improve and validate our previous work on drivers' manoeuvre classification using body posture data from a designed experiment [10] that includes drivers of different heights, seat preferences and levels of driving expertise. Secondly, we introduce a manoeuvre prediction scheme that can be learned with a data-driven approach from a general set of reduced manoeuvres, directly linked to HRI. Both results are achieved using shallow classifiers (i.e. SVM-W, Multi-layer perceptron, Extra trees), providing methods that are easy to replicate, validate and expand upon in future studies. Both results rely mainly on human-based data, enabling their application to other HRI where human behaviour can be measured online. Even though every single movement performed by human beings differs slightly from the next, human movements follow patterns and rules for learned tasks [11] (i.e. general movements do not differ between test subjects) and can be exploited to create dynamic relations and predict movements.

Compared to other work, our method relies mainly on body posture measurement and machine learning, which is much more suited to human modelling and prediction. Hence, we will show that we can interpolate and extrapolate models to other individuals for manoeuvre classification. We can predict up to 1.3 seconds in advance and interpolate prediction models within individuals. Extrapolation for prediction to unknown individuals is possible but fine-tuning with additional data is needed, which can be achieved thanks to the algorithms' retraining capabilities.

The remainder of the paper will be divided as follows: Section II explains the technical details of the proposed methodology, methods, experimental procedure, model training and validation procedure; Section III provides the followed procedure, results and discussion and Section IV shows conclusions and future work.

II. PROCESS

A. Experimental setup

In order to create, test and validate the models, data from test subjects whilst driving were gathered in a simulator. A generic driving experimental rig was used, similar to the ones in previous studies [12] [13] (i.e. automotive chair, Logitech G27 steering wheel with force feedback capabilities and pedals) together with a Kinect v2 sensor to record body posture. The driving environment was generated using Carmaker [14]. An automatic gearbox vehicle was simulated. A 21 inches LCD screen was used, with a viewing angle simulating a wide screen view and a speed gauge in kilometres superimposed on the screen. All data were collected at a sampling frequency of 30 Hz or time-step of 30 ms.

The driving task scenario was designed to replicate a road with successive turns, straight segments and a speed limit of 30 mph (i.e. built-up road). Eleven turns for each direction and straight segments in between were simulated. All tracks followed the British Design Manual for Roads and Bridges in terms of lane widths, curve radius and slope. The mentioned

speed limit was selected from available crash statistics in the UK, where most accidents occurred on built-up roads [15].

As the sensed body posture from the Kinect V2 depends greatly on limb and torso length, test subjects of different heights were selected to investigate whether models could work with people of different sizes, seat preferences and levels of driving expertise.

Test subjects had an initial conditioning stage to adjust driving skills from the real world to a simulated environment. Two sets of tracks with a Lane Change Task (LCT) of 1800 m [16] were introduced, where test subjects performed controlled lane changes; mean deviation (MDEV) from a normative lane change model [17] was calculated, with drivers repeating the test until achieving a MDEV < 0.7 m, as recommended by ISO (ISO/DIS 26022, 2010).

The experiment involved twenty-nine test subjects, seventeen females and twelve males. Driving experience was between 3 and 39 years, ($M = 9.36$ years ± 7.44 standard deviation (SD)); Chair position relative to sensor was between -1 and 17 cm, ($M = 5.52$ cm, ± 5.77 SD); Arm length was between 44 and 62 cm, ($M = 54.88$ cm, ± 3.88 SD); Torso length was between 38 and 53 cm, ($M = 43.24$ cm, ± 3.83 SD). None of the test subjects had previous experience with driving simulators, and the experiments had been approved by the Ethics Committee of the Faculty of Science, University of Bristol. Participants gave their informed written consent prior to participation. All participants confirmed to have normal or corrected-to-normal vision.

B. Automatic Manoeuvre Labelling

An automatic labelling process was created. All road sections were labelled based on the manoeuvre-based virtual map given by Carmaker; the virtual position of the car is then compared with the virtual map, in order to assign a label to the driver's data as seen in Figure 2. This approach allows to create precisely labelled datasets, reducing the variability of results that could be introduced by labelling errors and setting a clear threshold for manoeuvre transition.

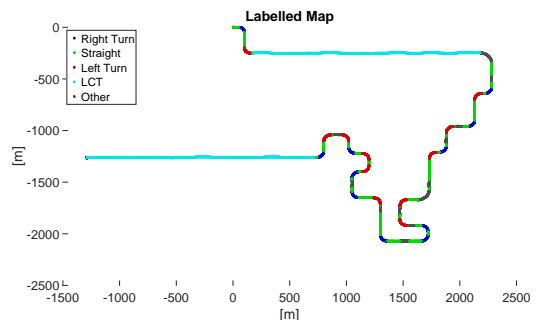


Fig. 2: Labelled road map

C. Manoeuvres state model

The idea of predicting a future manoeuvre comes from considering that there is a repeatable behaviour from manoeuvre to manoeuvre, inter and intra test subject, that can be reliably measured and reproduced numerically. This is related to general human movement tasks, where a task can

be divided into a smaller set of tasks that relate to the others, which can be seen as states and transitions.

In order to model the driving process into a finite state-transition model (i.e. Markov chain), a reduced set of manoeuvres was defined, with "driving straight" as the initial state, "left turn" and "right turn" as subsequent possible states and an equal state transition probability, as seen in Figure 3-a, which describes a driving scheme. Figure 3-b expands the driving scheme from Figure 3-a to predict manoeuvres, with "pre" manoeuvres for every type of turn-type manoeuvre (i.e. pre-left turn and pre-right turn). The assumption is that the same state transition probability from straight to other pre-manoevres is kept, enforcing that every pre-manoevre can only end in a turn manoeuvre. Getting to a pre-manoevre state always leads to a turn manoeuvre, allowing us to predict the manoeuvre itself.

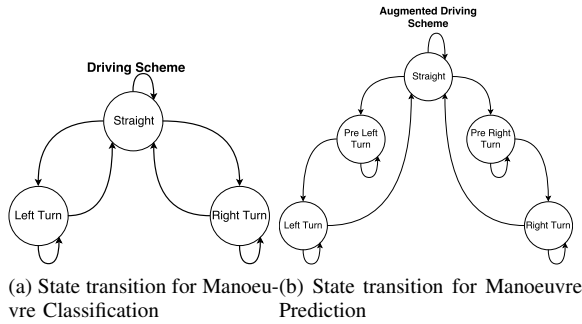


Fig. 3: Driving and Prediction state transition

To initially validate this idea, a certain trend must be seen in the data used for the manoeuvre classification, whether increasing or decreasing, starting in a certain value or range of values and ending in a specific range as well. The trend must be kept for a certain amount of time-steps Ts and theoretically diminish as the time-steps decrease.

Figure 4 shows the statistical analysis (average, confidence interval, outliers) of the used driving features (see [10]) for one individual test subject and for all grouped test subjects inside a time-window r . For the case of a single individual, data dispersion is less at $Ts = 0$, with a considerable number of outliers that increase as Ts approaches -90. For the case of all test subjects, data are highly variable and show big amount of outliers for all time-steps. The extensive noise is typical for skeletal tracking systems with occlusion (i.e. steering wheel); filtering techniques have proved successful to reduce noise and estimate joint parameters [18], yet we decided to prove that our methods can deal with this high level of noise without additional model-based methods (e.g. Kalman filter). In fact, the use of filters was not effective for the highly random noise.

D. Shallow Classifier models

Data-driven techniques have proven useful in HRI [19] and vehicle related tasks[20]. We focus on using three different classification algorithms, a kernel-based solution (Weighted Support Vector Machine), a perceptron based one (Multi-layer perceptron) and a tree based (Extra trees classifier) one.

A support vector machine (SVM)[21] finds optimal hyper-planes that maximize the separation margin between classes or the distance to the nearest training data points of any class, done in a high or infinite dimensional space. Main advantages of a kernel-based approach are its memory efficiency and effectiveness for medium datasets with high dimensional spaces. However, training time can grow exponentially with dataset size and it tends to over and under-fit for small datasets and over-unbalanced datasets.

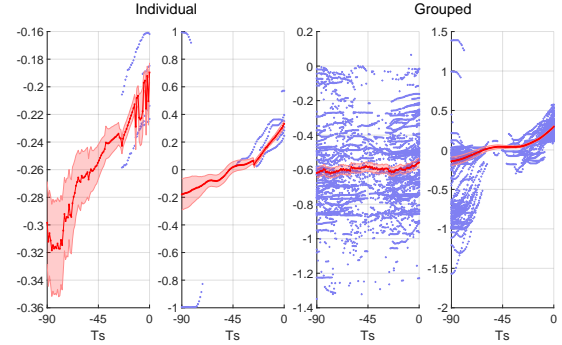


Fig. 4: Statistical analysis of left manoeuvre data (1 body-posture feature and steering wheel position). Time-steps Ts from 0 to 90 or 3 seconds before the manoeuvre is performed. Average (dark red), confidence interval (red area), outliers (blue)

Extra trees classifier (ET)[22] is a meta estimator based on decision trees, that fits several randomized decision trees on sub-samples of the training data, averaging its results to improve performance. Decision trees are models that learn simple decision rules, such as if-then-else rules, by recursively partitioning the training data and fitting similar decision rules at each subset[23]. Main advantages of tree-based approaches are its fast model creation, fast prediction time, easy to understand structure and the capability to evaluate the importance of the feature vector used to create the model. However, they tend to overfit and not being able to generalize well to unknown inputs.

Multi-layer perceptrons (MLP)[24] are neural networks that consist of layers of neurons that transform an input to a linearly separable space, effectively learning a non-linear function approximation for a specific value. Not different to regular neural networks, multi-layer networks can theoretically generalize any non-linear function. Main advantages of perceptron-based approaches are its capability of learning non-linear models, good scalability and the ability to learn online or be re-trained. However, they are extremely sensitive to initial conditions.

E. Training and validation procedure

A formulation of the proposed models is necessary to determine the entire training and validation process.

Models S^c or S^p will be created for classification or prediction purposes respectively. Models can be created using data from a single (S_i) or multiple ($S_{a,\dots,b}$) test subjects ts_i with $i = \{1, 2, \dots, N\}$ and $N = 29$; validation data can also be from one (ts_i^V) or many ($ts_{a,\dots,b}^V$) test subjects.

For **manoeuvre classification**, we start with a temporal set of features and a set of labels as the set of classifiable manoeuvres. The initial feature vector consisted of a reduced set of body posture features and driver input (i.e. steering wheel angle, throttle).

For **manoeuvre prediction**, we take the features from the classification manoeuvre scheme and augment it with the current manoeuvre estimation and vehicle speed. Moreover, we create a set of augmented labels similar to the ones for classification, with the addition of new classes that represent the pre-manoeuvre performed r time-steps before a turn manoeuvres (i.e. left and right turn).

A number of tests are proposed to validate the models around whether it can be used for known and/or unknown test subjects.

- 1) **Test 1, Interpolation using a model of one individual:** Evaluates individual models' feasibility and generalization capability to known test subjects.
- 2) **Test 2, Extrapolation using a model of one individual:** Evaluates individual models' generalization capability to unknown test subjects.
- 3) **Test 3, Interpolation using a concatenated model of various individuals:** Evaluates concatenated models' feasibility and generalization capability to known test subjects.
- 4) **Test 4, Extrapolation using a concatenated model of various individuals:** Evaluates concatenated models' generalization capability to unknown test subjects.

All results are evaluated using classification metrics (e.g. precision, recall, F1 score)[25].

Training and validation tests were done with stratified (i.e. separated by classes), randomized cross-validation sets, with 30% test data and 70% training data.

Manoeuvre prediction process considers an additional parameter, the fixed prediction time-window r . Initial validation showed that as r increases, data became more erratic, hence a successful prediction would become more difficult to achieve; also, data from different test subjects seems to show similar, yet not identical behaviour; such seemingly sparse data created a significant challenge to be generalizable. The set of fixed prediction time-windows $R = \{5, 10, 15, 20, 25, 30, 35, 40\}$ are selected to test this theory. A time-step between time-windows of 5 (160 ms) is enough time for both a controller to take action and a distinct behaviour to be shown by the driver.

The problem of class balancing is persistent during both processes. Turn and pre-turn manoeuvre data make around 4.5% to 25% of an entire dataset, generating a highly unbalanced dataset. An unbalanced dataset can produce models that miss to represent the less dominant classes or that overfits all classes in order to fit training data, as shown by obtaining low performance when tested against validation data. SVM-W and Extra trees have automatic sample-weighting mechanisms that mitigate the problem, but it does not guarantee an optimal solution. Two dataset balancing strategies are implemented: firstly, a random undersampler that reduces all non-pre-manoeuvre classes;

secondly, an under-over sampler which first undersamples the most dominant class (i.e. straight manoeuvre) to the level of the second most dominant class (i.e. left and/or right turn) to later oversample the pre-manoeuvre classes using a random sampler with replacement [26].

The dataset of each test subjects roughly contains the same amount of data-points (i.e. $9786 \pm 519SD$, 5% variation).

III. RESULTS

A. Manoeuvre Classification

SVM had the highest performance among the classifiers, hence its use for this task. An SVM without class balancing, standardized input, radial basis kernel and a multi-class strategy of one-vs-one is used.

1) **Test 1:** Both performance metrics scored high on average, with low variability between test subjects for all manoeuvres (see Table I). Results are always above 92% for all test subjects, which led us to believe that the data of all the test subjects can be used for manoeuvre classification.

TABLE I: Performance metrics statistics for Individual models

	Precision				Recall			
	max	min	mean	std	max	min	mean	std
Turn	0.99	0.93	0.98	0.012	0.99	0.96	0.98	0.007
Left	0.99	0.96	0.98	0.008	0.99	0.96	0.98	0.008
Straight	0.99	0.95	0.98	0.009	0.99	0.96	0.98	0.007
Right	0.99	0.95	0.98	0.009	0.99	0.96	0.98	0.007

2) **Test 2:** Most models were not able to classify the manoeuvres correctly, with less than five models managing to achieve precision and recall higher than 80%. This hints at the ability of the model to generalize even unknown test subjects with very few data-points. More data is needed to create a full model, as shown during test 3.

3) **Test 3:** Figure 5 shows the test results, with initial performance dropping as the model generalizes to new test subjects, but managing to stay above 95% for all metrics and manoeuvres during the entire procedure. Manoeuvre classification for known test subjects is feasible.

4) **Test 4:** Figure 6 shows the obtained mean precision between manoeuvres, showing good generalization after $S_{1,\dots,5}^c$, with average precision above 90% and above 95% after $S_{1,\dots,20}^c$.

Manoeuvre classification for known and unknown test subjects is feasible, achieving precision higher than 95%. As the estimation of \hat{y}^c is validated, the creation of a model to predict future manoeuvres can be attempted.

B. Manoeuvre Prediction

All three proposed algorithms were used for manoeuvre prediction evaluation. An F1-based hyper-parameter optimization was done for all the proposed algorithms; this approach produced better results compared to a precision or recall-based optimization. Other used parameters were: SVM-W with standardized input, radial basis kernel and a multi-class strategy of one-vs-one; Extra Trees Classifier with 10 estimators and minimum sample for leaf of 2; Multi-layer perceptron (MLP) with rectified linear unit (ReLU)

activation function and cross-entropy loss function. SVM-W and Extra trees' Balancing options are set with class weights inversely proportional to the frequency of a class. Among the class balancing options, under+over sampling was the best performing technique. Hence, only this method is being discussed.

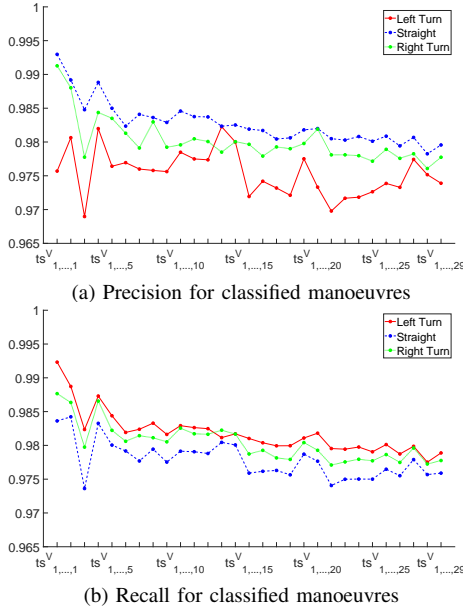


Fig. 5: Metrics for concatenated models $S_{a,\dots,b}^c$ tested against $ts_{a,\dots,b}^V$ for $a = 1$ and $b = \{1, 2, \dots, N\}$

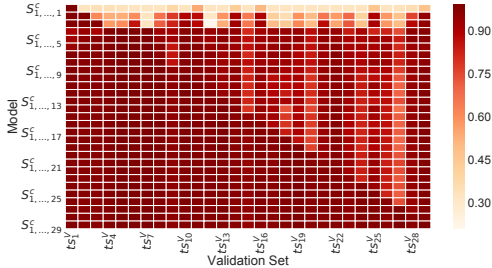


Fig. 6: $S_{a,\dots,b}^c$ mean precision for $a = 1$ and $b = \{1, 2, \dots, N\}$ against ts_i^V for all $i = \{1, 2, \dots, N\}$

1) **Test 1:** Figures 7 and 8 show the respective average precision and recall between both pre-manoevres and all test subjects, averaged for each time-step; maximum and minimum values, as well as the standard deviation of the averaged results are displayed. General behaviour coincided with initial hypothesis and the analysis shown in Figure 4, with better overall performance for short time-windows and decreasing and more disperse results as the time-window increases. SVM-W outperformed MLP and ET in both precision and recall but took more than 10 times the time it took to train the other models; ET was the second best performing model and the fastest one to train, with MLP being the least performing and second most efficient one to be trained. Individual models are shown to work for known test subjects and the specified parameters.

2) **Test 2:** Similar to manoeuvre classification, most metrics are well below 70% even for short time-windows.

Among the classifiers, SVM-W and MLP seem to generalize its results better. Performance still decreased as time-window increased. These results are linked to data shown in Figure 4, with pre-manoevre behaviour being vastly different between test subjects, which could be solved by including data of more test subjects, as it happened previously.

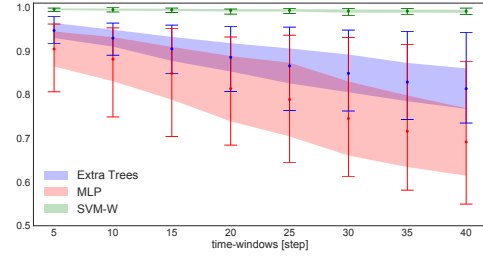


Fig. 7: Statistical analysis of precision metric for model S_i^p tested against ts_i^V for $i = 1, 2, \dots, N$. Average for all i (dot), standard deviation (shaded area), max and min values (caps)

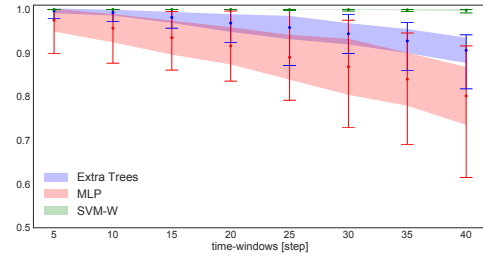


Fig. 8: Statistical analysis of recall metric for model S_i^p tested against ts_i^V for $i = 1, 2, \dots, N$. Average for all i (dot), standard deviation (shaded area), max and min values (caps)

3) **Test 3:** Figures 9 and 10 show the results of a model including data from all test subjects or $ts_{1,\dots,29}$. Results are consistent with the individual models explained in Figures 7 and 8; SVM performs the best, followed by ET and MLP models with performance drop whilst time-window increases. Manoeuvre prediction for all known test subjects for the proposed time-windows is shown to be feasible.

4) **Test 4:** None of the created models managed to generalize to any random, unknown test subject. Some combinations of concatenated models and unknown test subjects managed to produce results with metrics over 80%, which point towards the possibility of achieving this goal, yet precision and recall are well under 40% in general; patterns were seen in these combinations, some around body shape (i.e. similar arm length) and others around driving style aspects of it (e.g. mean and max vehicle velocity before a manoeuvre), both reasonable results related to the type of data being used (i.e. body posture) and the task at hand (i.e. predicting a highly dynamic and user-dependant task).

Considering the results from Test 2 and Test 3, manoeuvre prediction can be done for more than one test subject. A straightforward solution for predicting more test subjects is to add data from new drivers. Although SVM scored the highest scores, its long training times would make this proposed solution more difficult to implement; in comparison, ET and MLP enable it by providing fast training times (ET) and re-training or online training capabilities (MLP); this

solution would fit well in a user-interface that includes a customization or calibration-like phase to the system.

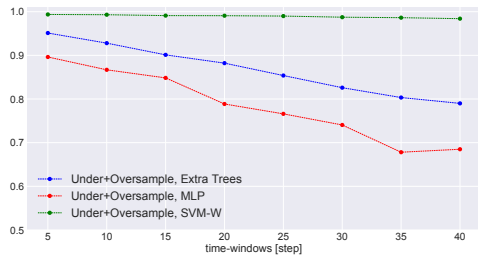


Fig. 9: Precision for model $S_{1,\dots,29}^p$ tested against $ts_{1,\dots,29}$.

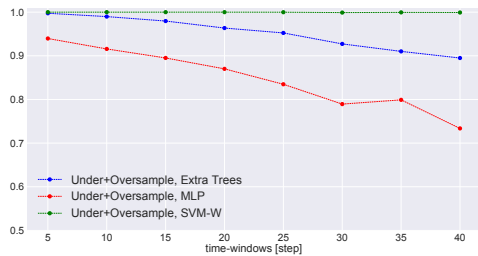


Fig. 10: Recall for model $S_{1,\dots,29}^p$ tested against $ts_{1,\dots,29}$.

IV. CONCLUSIONS

The concept of intended driver manoeuvre prediction using current manoeuvre estimations was introduced. Body posture information from drivers of different sizes, seat preferences and levels of driving expertise was used together with vehicle speed, applying strategies originally introduced for human-robot-interaction (HRI) to human-vehicle interaction (HVI). The success of the methods here presented are aimed to serve as a parallel between HVI and general HRI by taking advantage of data gathered from both agents (e.g. body posture for human, velocity for vehicle) and the definition of a well bounded and structured task.

Initially, the idea of manoeuvre classification was revised. Models scored precision and recall scores higher than 95%, in contrast to 88% on previous work [10]. Results were validated for known and unknown test subjects.

As a second step, the concept of manoeuvre prediction was introduced. Models capable of predicting manoeuvres for fixed time-windows as big as 1.3s were found to be feasible for known test subjects, with precision and recall higher than 90%. Three different algorithms were used for the task, two of them able to add new user data with very short training time or to be trained online; these latter algorithms could be used together with a user protocol that allows to quickly calibrate the models for new drivers. However, none of the models could predict new drivers without recalibration.

Further work will include more sensors (e.g. heart rate, eye gaze) to investigate whether such information allows models to predict manoeuvres of unknown drivers. Extra material is available online (i.e. video and labelled datasets [27]).

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