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Estimation of longitudinal speed profile of car drivers via bio-inspired mirroring mechanism

G. Valenti
Department
Industrial Engineering
University of Trento
via Sommarive, 9, Trento, I-38123
Email: giammarco.valenti@unitn.it

L. De Pascali
Department
Industrial Engineering
University of Trento
via Sommarive, 9, Trento, I-38123
Email: luca.depascali@unitn.it

F. Biral
Department
Industrial Engineering
University of Trento
via Sommarive, 9, Trento, I-38123
Email: francesco.biral@unitn.it

***Abstract*—This paper deals with the problem of the prediction of driver intention. The problem is relevant in the context of modern Advanced Driver Assistance Systems. More specifically, we address the task to continuously generate a predicted longitudinal velocity profile with a fixed time horizon and associated with a driver's intention (e.g. overtake). The objective is to obtain a "general purpose" prediction, aimed to feed any ADAS algorithm requiring future longitudinal velocity and intention informations, like safety applications, warning systems or MPC-based algorithms. The prediction makes use of the artificial co-driver concept, which is here designed to deal with longitudinal inputs only. The co-driver is an agent able to perform inference of intention by means of a mirroring approach, trying to imitate the human driving behavior. The approach is conceived to be simple and modular, using only longitudinal informations from the vehicle, and flexible to the availability of external informations (e.g. vehicle ahead). The works includes the implementation of a jerk filtering technique proposed by some of the authors, this technique is used in a mirroring approach for the first time. Preliminary results on prediction are presented, and future development and validation are discussed.**

***Index Terms*—Advanced driver assistance systems, driver modeling, inference of intention.**

I. Introduction

This paper addresses the problem to infer the intention of drivers in terms of longitudinal maneuvers with an accurate prediction of the future longitudinal speed profile for the longest time horizon possible. Predicting in advanced the driver's intention (*e.g.* following a front obstacle, achieving a desired target speed, etc), is a critical task in the development of Advanced Driving Assistance Systems (ADAS) up to application of type L3 (according to SAE autonomous driving nomenclature). Properly inferring the maneuvers goal beforehand allows to timely deliver warning messages and intervention to support the driver to safely and comfortably accomplish his/her desired maneuver. Additionally an highly accurate estimation minimizes false alarms or, even more important, missed alarms or intervention improving driving experience. In this context knowing ahead of time not only the intention but also the desired future speed profile makes it possible to quantitatively assist the driver and improve his/her maneuver whenever necessary (*e.g.* brake more if driver's safety is put at risk) as well as optimize drive-line response or energy management of hybrid or purely electric vehicles. However, obtaining an accurate estimation on long time horizon is a challenging task since the speed profile is affected by many factors including the driver's possibility to change his/her short term goals, and therefore maneuver, or the urgency to adapt to unexpected situations. In this work the time horizon of the speed profile prediction is the short-term one, (up to 10 seconds), aiming to reach quite high accuracy. Behind this objective there is the hypothesis of the driver to be following one intention only, and predicting simultaneously the intention and the velocity profile that will generate from it.

Due to the importance of the task the literature on drivers' intention estimation is rich and vast. A family of approaches is based on behavioral pattern recognition and classification [1], [2] making use of learning machine based methods such as Support Vector Machine, Hidden Markov Models. A limitation of classification models is their inability to explicitly explain why and how the driver takes an action to follow his/her intention. Generative approach is an alternative method that makes multiple driving hypothesis among which the most probable one is selected from the observations of the actual driver behavior. Intelligent Driver Model is a physical based approach that compares a number of longitudinal motion hypotheses to infer the drive intentions, [3]. A quite recent research stream in this field is based on the use of Deep Neural Network, in particular recurrent and LSTM networks, that fuses the sensory information and learns to anticipate the sensorial input [4] or formulate driver action prediction as a time series anomaly prediction problem [5]. The paradigm used here is still generative but with a different meaning inspired by the "mirroring" concept from the most recent findings in the cognitive science [6], [7]. The artificial mirroring process consists in using an external agent that runs in parallel with the human trying to imitate his/her behavior to understand the scenario and take the desired action via a selection mechanism of a set of continuously generated behaviors/actions that optimally achieve a number of different goals. The use of generative approaches in context of inference of human actions is both biologically motivated [8] and provide some immediate advantages. The practical advantages lie in the possibilities to infer and generate behaviors simultaneously. This main characteristic of the generative approaches allows the agent to directly intervene with the correct action (maneuver in the driving case) in case it is necessary, being the correct maneuver already generated, and the mirroring agent *knows* how to behave even if the mirrored one (i.e. the human) does not.

The generation of the goals is strongly related to the context since they are hypotheses of feasible and optimal actions (i.e. *affordance*) suggested by the context and surrounding objects [9]. This allows to conceive a restricted set of possible goals, and the action selection mechanism as a competition between those possible affordances [10]. The mirroring process is the discovery of the affordance that best matches the current ongoing human action (e.g. longitudinal maneuver in this work).

A. Related work

The theoretical basis for the proposed approach for the driving task was introduced as the concept of artificial co-driver in [11] for normal driving support and specifically for intersection support in [12]. Here the mirroring mechanism makes use of semi-analytical solution of minimum jerk longitudinal maneuvers, which are simultaneously generated to reach various goals (*e.g.* free flow, follow a car, etc) to infer the driver intended maneuver via the selection of the one that best matches the driver's intentional longitudinal jerk ,which is used as a characterizing input of the longitudinal dynamics produced by the human driver. Therefore, the actual driver's intentional longitudinal jerk needs to be estimated and it is here achieved using a minimum set of on-board sensors and the observer proposed in [13]. Minimum jerk maneuvers are also adopted in [14] in the form of a quintic polynomial that represents the solution of related optimal control problem but it does not apply the generative approach and looks for the on-line identification of the polynomial coefficients that match the driver's actual maneuver only.

The paper is organized as follows. In Section II The co-driver concept and its theoretical foundations are presented: The co-driver basic definition in term of agent abilities is provided, and cognitive theories which the co-driver concept is based on are presented. In Section III the co-driver realization used in this framework is discussed, the proposed specific architecture is exploited: every functional block of the architecture is explained, from the jerk filtering of [13] which is contextualized in the architecture, throughout the action priming and the action selection mechanisms. In the last sections IV and V some preliminary results are shown and discussed and the algorithm is tested in a dataset of naturalistic driving. Some examples are extracted in order to show the potential of the algorithm.

II. CO-DRIVER CONCEPT

A. Co-drivers concept

An artificial Co-driver in this context is defined as an agent able both to *drive* like a human and to *interpret* his/her driving intentions [11]. An intuitive example to understand this concept is to think the co-driver as a driving license tutor: the tutor is not only able to *drive* like humans, but s/he has also to anticipate the trainees actions by *interpreting* their intentions in order to intervene in emergency situations to correct a mistake through the auxiliary vehicle controls. In this analogy, the relation between the driver (trainee) and who is playing the co-driver role (the tutor) is made of a mutual and continuous feedback relation. It is worth to notice that, since the co-driver agent is aware of the driver's goals it actively intervenes only when it is necessary. Active inference of drivers' intentions from the artificial co-drivers without interfering with his/her goal may be an important intermediate step towards the acceptance of advanced autonomous agents into a delicate and dangerous task like driving. Action prediction (interpret intentions) and action generation (drive) are the coupled tasks that characterize a co-driver. In [15] the *simulation theory of cognition* is proposed, which is a cognitive theory that simultaneously takes the synthesis and the analysis of behaviors into account. In other words it explains who an external agent predicts what the driver is going to do and how it would drive in the same situation. The basic building blocks of this theory are the action-perception loops: thinking is conceived as a *simulation* of sensory-motor loops, meaning that cognition can be represented by cyclic activation of motor and sensory structures. The activation of the structures is the same as in an overt action, but the actual execution of the action (motor structures) is covert. This synthesis mechanism can become an analysis mechanism as long as the simulated sensory-motor loops can work as emulation of observed behaviors. This method is typically called "mirroring", and it is the mechanism adopted in the proposed inference method. In this framework seeing through the intention of the driver is then a simulation process carried out via the mirroring process, which is further detailed in the Section II-B.

B. Co-drivers general structure

Co-Drivers are a broad category of possible systems that, as stated previously, are able to drive like a human and infer his/her intention. The first task this agent has to accomplish is then to *drive like a human*. The mirroring agent used in this paper is based on a model introduced by Hurley in [8]: the shared circuit model. This model accounts for the synthesis of the human behaviors and for the mirroring process, as depicted in figure 1 indeed, the reference structure consists in two loops. Generation of human-like behaviors (driving) concerns the inner loop (mirroring agent loop), where two substructures are defined:

- Forward emulators
- Inverse models

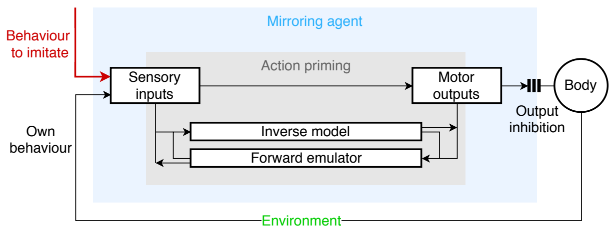


Fig. 1. Representation of the shared circuit model: the action priming block generates the sensory-motor loops, while the mirroring agent performs action selection trying to perform imitation.

The forward emulator is the block that models how the environment behaves as consequence of a simulated action (i.e. how the sensory part of the cognitive system would react if it was able to sense the consequences of the simulated action, because between the cognitive system and the environment there is a perception layer). This block represents how the human imagines his/her own action will affect the environment and the objects involved. In our framework, the forward model consists of the way the driver figures the vehicle response, as it is done in [11]. The inverse models play a different role, while the forward emulator models the consequences of an action (during the action execution), the inverse models link a goal to the necessary action. Represent "how" the action is performed, acting in the opposite direction. Inverse models are closely related to the concept of affordance [9]. An affordance is a potential behaviour/action that can be executed to interact with an object/situation. Therefore, inverse models serve to generate human-like affordances. For instance if there is a car ahead, a possible affordance is overtaking it and the inverse model consists in the set of rules according to which such action takes place. In our framework, the elementary affordances are the longitudinal motion primitives (see Section III-C). The forward emulator is the model of the closed-loop system between the human and the longitudinal dynamics of the vehicle [11], which result in a triple integrator. The inverse models are the optimality criteria of the human longitudinal driving (see Section III-C).

III. Proposed architecture

In this section the proposed architecture is explained. The Co-Driver concepts can be declined in a broad variety of possible systems. Here, the architecture is designed to imitate the driver behavior for controlling the longitudinal dynamics in order to predict the future velocity profile.

A. Co-Driver main architecture

An overview of the functional blocks of the architecture of the Co-Driver is shown in Figure 2. The first block is a jerk filter used to estimate the intentional acceleration and jerk (acceleration time derivative). Intentional jerk is the one that should correspond to the target maneuver the driver has in mind without the effect of disturbances introduced by the environment or the dynamics unknown to the driver (e.g. clutch intervention, road uneveness, etc). The filter, implemented as in [13], yields as output the vector:

$$\begin{bmatrix} v & a_i & o_a & j_i \end{bmatrix}^\top . \tag{1}$$

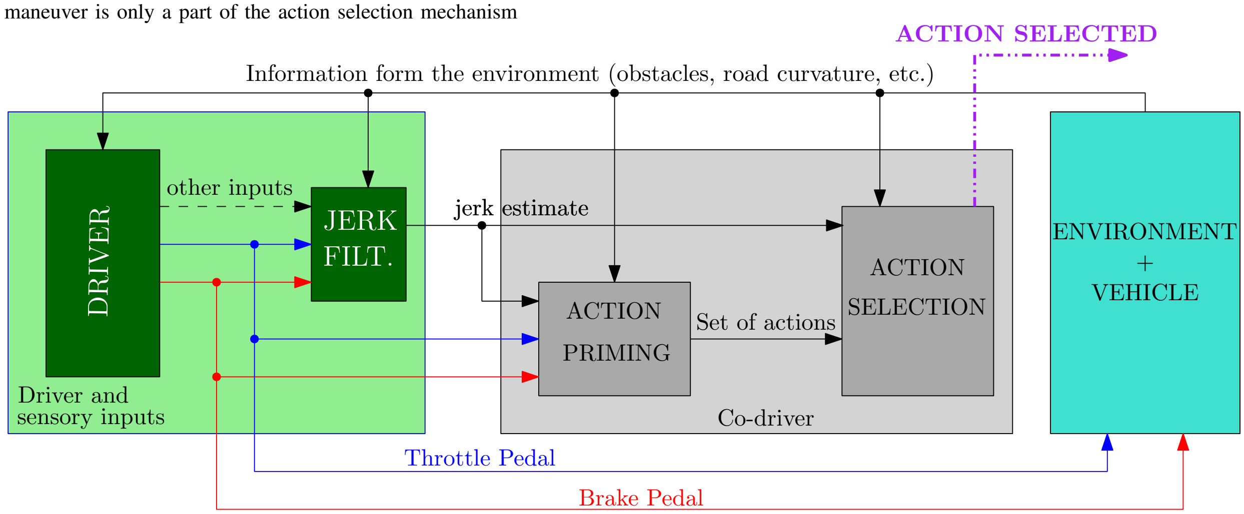
Where v is the longitudinal velocity of the vehicle, a_i is the intentional acceleration, o_a is an estimated offset of the acceleration in which the slope of the road and the misalignment of the accelerometer are included, j_i is the intentional jerk. The intentional acceleration a_i is, as the name suggest, an acceleration the driver requires via the gas pedal as direct torque request. The jerk filter is designed to filter out the mismatches of acceleration due to a difference from the torque request and the actual torque provided [13] (e.g. the engine cannot provide all the requested torque). The action generation block uses the velocity and intentional acceleration of the driven vehicle (which is the vector $\begin{bmatrix} v & a_i \end{bmatrix}$) as initial conditions for the generated reference maneuvers (action priming). Instead the intentional jerk is used in the action selection block only, since it is more representative of the high-level intentions [13]. Note that this stage represents the inner loop of figure 1, the action priming make use of the inverse models and the forward emulator (see Section III-C). The action selection mechanism is the stage where the covert action is selected, based on different metrics which are explained in Section III-E).

B. Action priming

The core of the mirroring process is based on the generation of a set of human-like maneuvers for the longitudinal dynamics (i.e. action priming). The set of longitudinal maneuvers is based on the affordances the environment suggests (i.e. possible manoeuvers),each of which is expressed in terms of specific "goal". An array of channels is defined where every channel is associated with a possible longitudinal driving manoeuver always associated to the same goal. The channels are introduced to connect an index to every goal and to keep it in the same order. In this work the goals are chosen as the simplest affordances in the longitudinal driving, thinking about situations of open road and the possibility of the presence of another vehicle. The affordances are listed in the related column of the Table I.

The manoeuver associated to each goal is build on the set of longitudinal motion primitives. The initial conditions for the motion primitives are the "intentional kinematics" of the driven vehicle, (estimated by the intentional jerk filter) $\begin{bmatrix} v & a_i \end{bmatrix}$ whereas the final conditions depend on the goals. Motion primitives are considered to be elementary maneuvers (or affordances)in the longitudinal driving. They can be combined to create more complex behaviours. For instance, a free road would suggest affordances to reach a target velocity, a car in the lane would suggest the affordance to be followed. In the next section we describe the fundamental unit of the longitudinal driving actions: the longitudinal motion primitive, introduced in [11]. They consist in elementary longitudinal maneuvers to obtain short term goals (e.g. reaching a velocity).

Fig. 2. Co-Driver main architecture. Three main building blocks are present. The environment block is connected with the action generation block and the action selection block because the mirroring process of the Co-Driver implies the autonomous maneouvre generation and inhibition, the similarity to the human maneuver is only a part of the action selection mechanism



In a cognitive sense they represent the simplest sensory motor loops we use in this framework.

C. Longitudinal motion primitives

Motion primitives are derived based on the experimental evidence that humans plan the longitudinal dynamics minimizing the jerk. Here it is assumed that the longitudinal jerk is the input the driver uses to control the vehicle. The assumption is based on the observation that the driver can sense the rate of change of the gas pedal, which is proportional to the change of the requested torque and therefore the jerk. It is also assumed that humans adopt in the planning task a "simplified" dynamics of the vehicle they are driving (known as forward emulator), leaving the most complex non linearities to a low level controller in the neural system. Therefore a kinematic model is used, shown in Equation (2),

$$\dot{s}(t) = v(t) \quad \dot{v}(t) = a(t) \quad \dot{a}(t) = j(t) \tag{2}$$

where: $\boldsymbol{x}(t) = \begin{bmatrix} s(t) & v(t) & a(t) \end{bmatrix}^\top$ is the state vector and its elements are position, velocity and acceleration respectively. The term $j(t)$ denotes the jerk (input). The position $s(t)$ is intended as the traveled distance $v(t)$ and $a(t)$ are the velocity and acceleration along the trajectory respectively.

Given the forward emulator the inverse dynamic problem can be solved (i.e inverse model) to understand the human planning of the longitudinal maneuver. It can be formulated as an Optimal Control Problem:

$$\min_{j(t)} J \quad s.t. \quad (2), (3c), (3d) \tag{3a}$$

$$J = \int_0^T \left(w_T + j^2\right) dt \tag{3b}$$

$$\boldsymbol{x}(0) = \begin{bmatrix} s_0 & v_0 & a_0 \end{bmatrix}^\top \tag{3c}$$

$$\boldsymbol{x}(T) = \begin{bmatrix} s_f & v_f & a_f \end{bmatrix}^\top \tag{3d}$$

The functional J in 3b, has a term j^2, which model the human optimality criterium that minimizes the control signal itself. The other term w_T is a weighting factor on the final time T of the primitive, note that the time T is free. It is used to model the urgency of the maneuver. The initial conditions are the following:

$$s_0 = 0 \quad v_0 = v \quad a_0 = a_i, \tag{4}$$

where v is the measured velocity of the vehicle, and a_i is the intentional acceleration carried out by the jerk filter in [13], (see Section I-A).

D. Primitives priming

Problem 3 can model various family of longitudinal maneuvers properly setting the final state or conditions $\boldsymbol{x}(T)$, and the parameter w_T. The final conditions of each primitive is related with the desired goal. Two important aspects of the primitives priming are introduced in this architecture:

- The maneuvers (primitives) are generated in terms of their goals and their parameters in a finite number.
- The actions are ordered in channels, every channel is associated always with the same goal.

The reader may note that the architecture is scalable and can be extend with new affordances (i.e potential maneuverers) or some affordance can be replaced with more representative ones (eg. combining two affordances). Some example of affordances (associated with primitives) are listed in table I. Some of them require informations of the state of the directly involved objects: for instance the overtake maneuver and the follow object maneuver, require the initial distance s_0 of the front vehicle. The primitives are parametrized. However, a different parameter does not change the nature of the affordance but only how it is implemented. For example, the w_T is the time-weight and t_h is the time-headway between the vehicle to follow and the ego vehicle. Different values of these parameters means adapting to the front obstacle speed in less/more time and with less/more time headway.

The generated maneuvers are divided into channels, every channel corresponds to a goal. A goal includes the final state of the maneuver (final speed , final acceleration , and, in some cases final relative position), and the time-related parameter w_T. A channel can share the same final conditions with another one but have different time-weight term w_T. The association channel-goal-maneuver is fixed in time. It means the number of possible affordances does not change with time, When a goal cannot be generated, (for example an overtaking maneuver in case no vehicles to overtake are present), the channel is simply inhibited. The goal-oriented action priming has two main reasons adopted for action selection:

- The action selection mechanism can be performed with a decision-making paradigm, since a channel is associated with a goal and then keeping the same channel means keeping the same goal.
- The re-planning of maneuvers can account for a non-perfect following of the maneuver itself, and following a primitive become a re-planning of the same primitive with new initial conditions. If the goal holds, the maneuver associated with it is generated with the new initial conditions. This is visible in Figure 4 in which is possible to recognize slightly different consecutive maneuvers with the same goal, they appears in "bands" in the plots.

E. Action selection

Once the affordances are generated, the next step is to model the action selection mechanism. The overall goal is to identify the manoeuver that produces the control input (the jerk) that best match the one produced by the driver and estimated by the filter. To this end the generated actions, the affordances, are mapped along their instant control effort: the initial longitudinal jerk, j_0. The axis j_0 is the abscissa in which a function is defined: the motor cortex. The motor cortex is the very first *score* which is assigned to a single affordance. The motor cortex (mc) is mapped in the j_0 axis, and it is then a function of it:

$$mc = f(j_0) \tag{5}$$

The motor cortex abscissa is isomorphic with the field of view in a longitudinal sense, it means the higher the value in the abscissa of an affordance, the farther the point your inverse model of the vehicle reaches keeping that control constant (j_0), in the same way in [11] the control metric space is isomorphic in both the direction. It is intuitive if one think about the role of the jerk as the control signal in the triple integrator "inverse model". The motor cortex represents what is called the "primary motor cortex" in [10]. The function for the motor cortex is defined based on the aim to imitate and understand the driver. Therefore, the function is designed to highlight the perfect imitation when the intentional jerk j_i and the affordance jerk j_0 are identical. The function is:

$$mc_{0,k}\left(j_{0,k}, j_i\right) = \frac{1}{(j_0 - j_i)^2 + 1} \tag{6}$$

this function is proportional to the jerk error, in a quadratic sense and the maximum is $mc(j_0 = j_i) = 1$. The number of channels is discrete, then the motor cortex is an array of values with the same length of the channels where the index k indicates the number of the channel. The co-driver must also have the intelligence to prioritize some generated maneuvers basing on its context knowledge. This is implemented with a biasing procedure of the motor cortex, inspired by the biological biasing occurring in the fronto-parietal system of the brain [10] The biasing consists in the multiplication element by element times an array of each channel's motor cortex value, obtaining the biased motor cortex bmc.

$$bmc_k = g_k \cdot mc_k \tag{7}$$

Biologically, biases can have a variety of different causes, from direct sensory inputs, to strong inhibition due to logical reasoning, to rewards from longer-term goal to reach. In order to simulate and manage the complexity of the biasing causes, the adopted approach is to use *layers* of biasing, which is actually very similar to what occurs in the fronto-parietal system of the brain in the affordances competition hypothesis framework [10]. Potentially the biases to introduce are infinite. We introduced 4 biases based on intuitive considerations on longitudinal driving that are:

- The *brake* bias: it relies on the information about which pedal is pressed (throttle or the brake pedal) and it is based on the following assumptions: if the driver is pressing the brake pedal the target velocity of the maneuver must be lower than the initial one. This bias is a strong inhibition, it sets to zero all the gains of maneuvers which has target velocity higher than the initial one.
- The *reasonable target velocity* bias: it selects the maximum velocity allowed in the future path v_{max} (with an horizon compatible with the prediction), and set the gains as a function of the target velocity of each manoevure, given $v_{f,k}$ as the target velocity of the manouvre k, penalizing primitives with $v_f > v_{max}$, v_{max} depends also on curvature according to the two third law [16]. The parameters p and v_{margin} are related to the length and the slope of the decreasing part of the curve $g_k(v_{f,k})$.
- *Interaction* bias: the primitives related to the interaction with obstacle vehicle are inhibited setting null gains, when the obstacle is not present within a certain distance.
- *Minimum instantaneous jerk* assigns the gains directly related to the initial jerk of each maneuver. The function here is based the distribution of the jerk in [12], (Fig 11). This bias represents the prior distribution of the jerk.

The action selection mechanism, in term of functional blocks, is shown in Figure 3. The last part of this Co-Driver's action selection mechanism, is the block playing the role of the basal ganglia (according the biological analogy). This block receives in input the biased motor cortex (bmc), which is an array with the bmc values for each channel. In the basal ganglia one of the affordances (channels) has to be selected. In this co-driver the selected action is the one with the higher biased motor

TABLE I

LIST OF AFFORDANCES REPRESENTED BY THE PRIMITIVES. THIS LIST CONTAINS ALL THE AFFORDANCES USED IN THE CO-DRIVER ARCHITECTURE OF THIS PAPER. ARBITRARY NEW AFFORDANCES CAN BE ADDED.

Short name	Affordance	Final conditions	Free parameters
Keep Flow	Keep the current speed v_0	$a_f = 0 \;\; v_f = v_0 \;\; s_f = free$	w_T
Free Flow	Reach a desired speed v_d	$a_f = 0 \;\; v_f = v_d \;\; s_f = free$	w_T, v_d
OverTake	Overtake a host vehicle at velocity v_d	$a_f = 0 \;\; v_f = v_d \;\; s_f = s_0 + v_h \cdot (T)$	w_T, v_d
Follow Object	Follow a host vehicle which travels at v_h	$a_f = 0 \;\; v_f = v_h \;\; s_f = s_0 + v_h \cdot (T + t_h)$	w_T, t_h

cortex.

$$k_{selected} = argmax_k\,(bmc_k) \tag{8}$$

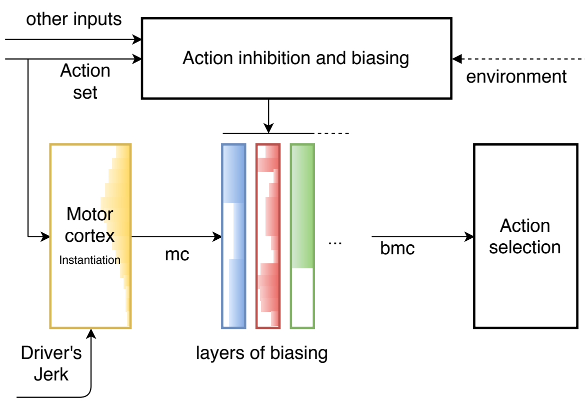


Fig. 3. Action selection mechanism: the first instantiation of the motor cortex is done with the function in (6). The biased motor cortex (bmc) is obtained through the multiplication times the gains of the biasing, the arrays of the gains are introduced from different source. The green layer of bias is an example of strong action inhibition, in which entire portion of motor cortex are set to zero (pedals input example), the other two colors represents different cases, the red is more unrelated to the jerk. The last block performs the final selection (playing the role of the basal ganglia)

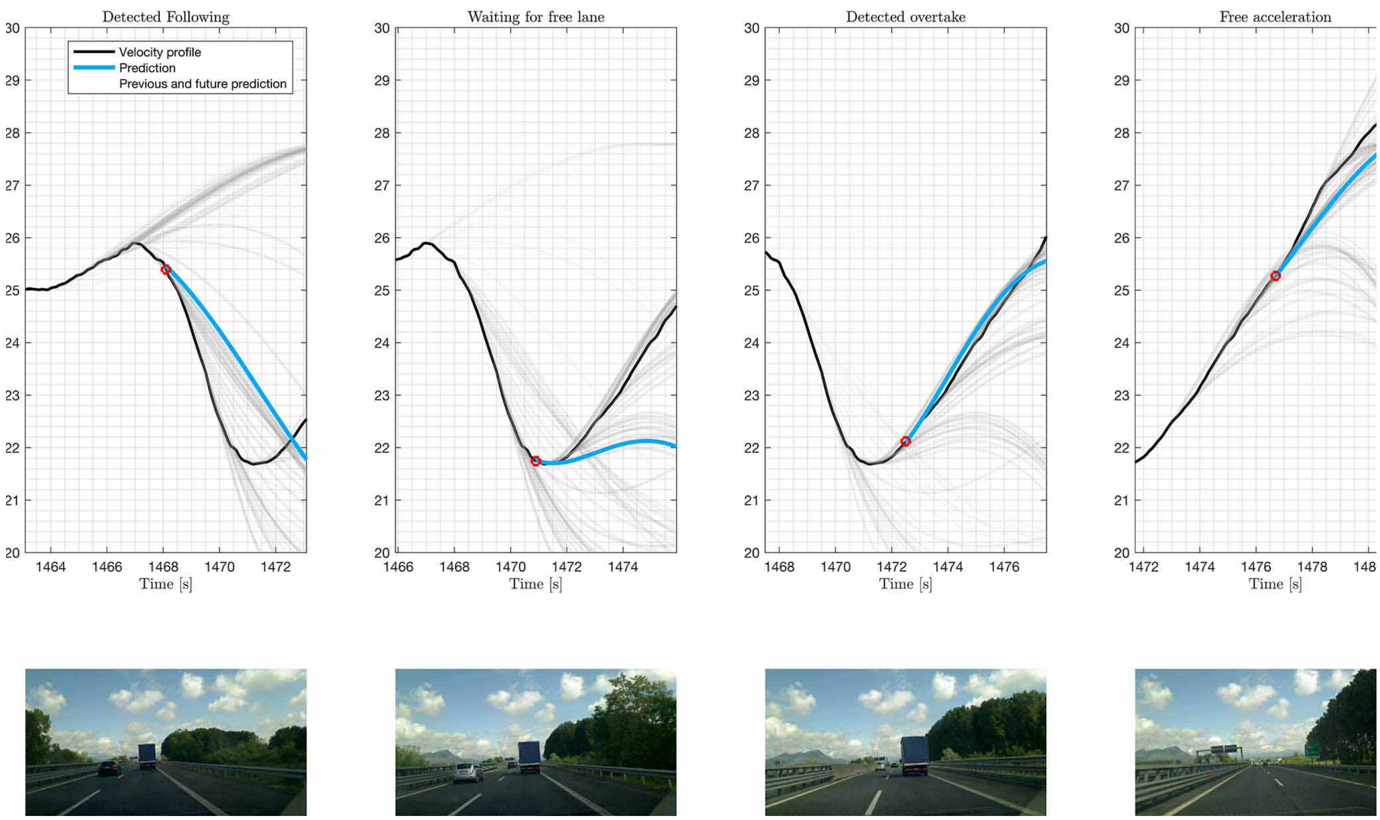
IV. PRELIMINARY RESULTS

The performance of the method here proposed was assessed running the algorithm on a small subset of on a naturalistic driving dataset involving urban, extra urban and motorway driving scenarios. We report some preliminary results but additional data and deeper investigations will be done in the future. Figure 4 shows examples of predictions and the instant when the system detects the change of intent of the driver. The road presents two lanes, ego vehicle is on the right lane. A truck traveling at lower speed is present in the same lane of the ego vehicle. The left lane is not free at the beginning and this scenario represents a salient situation to show the operation of the co-driver. In the results four consecutive intention predictions are highlighted (thick blue lines), with qualitative different velocity prediction accuracy, whereas in light gray the manoeuvres of the previous and following predictions are represented. In this example, four different goals are detected sequentially (and their respective goal keeping during updates). From left to right in Figure 4, in the first plot the intention of following the truck ahead is detected, with a desired time headway of 1 second. In the second the intention switch to the same kind of maneuver, but with a time headway of 0.5 seconds, we associated this low acceleration maneuver (getting closer to the truck) to the intention of waiting for the left lane to be free getting ready for an overtake. The overtake intention is detected in the third plot with a good accuracy in the velocity. The overtake turns into an intention to reach a velocity in a ”free flow” fashion (no constraints in final position in the maneuver). The velocity aimed to reach is greater than the one predicted in the overtake phase, since the lane is free and the driver starts to accelerate for longer. It is worth to notice that from left to right the first example represents a correct goal detection but it is the less accurate velocity profile prediction compared to the others. The reason can be attributed in an slightly changing in the intention, in order to make more room to perform the ”waiting phase” for the overtake, in this case the re-planning in the same channels allows a better fitting in the next instants (see gray curves). The second case represents a very short term goal, in which the intention is consistent for 1-2 seconds only, for which longer prediction is not possible keeping only one goal into account. The other two plots represents correct predictions, either in term of velocity profiling and intention detection, the last presents a small error due to a future relatively sudden change in acceleration, which cause an offset in velocity prediction. In Figure 4, other predictions are shown as light gray curves. From those curves is possible to recognize the continuous update of the primitives, when they share the same goal the primitives are similar. Since the number of generated primitives is finite the goal-oriented approach allows to adjust the primitives if real parameters are slightly different but the goal is consistent. This is clearly visible in the first plot of the figure, when there is no primitive to represent perfectly the particular “following object” behavior of the driver, but the updating allows to gradually improve the fitting.

V. CONCLUSIONS AND FURTHER RESEARCH

This work proposes a realization of the co-driver concept [11] aimed to accomplish the task to be a general-purpose predictor of velocity profile and longitudinal intentions. The preliminary results show the potential of our approach to deal with such task, making the predicted profile suitable for various applications. The results are not aimed to be a validation of the approach, but only an example to show the operation of the algorithm. The approach is relatively simple, signals-aware and modular (In Section III it was shown the modularity of both the action priming and the action selection). The results also show the current limitations on the accuracy

Fig. 4. Prediction examples. From left to right: The intention to follow the truck with 1 second of time headway is detected the intention is correct but the accuracy of the velocity profile is less accurate than the ones in other predictions. The second plot shows a maneuver aimed to change the time headway with the truck (getting closer), waiting for the left lane to be free, the prediction here is quite accurate for the time the intention hold (short time). In the third the overtake intention is detected, turning into a free acceleration maneuver (”free flow”) in the last plot.



of the velocity profile, mainly due to the necessity to use a finite number of possible goals. Wide margin of improvement are present, from jerk estimation to the ”design” of the motor cortex. The modular nature of this approach, allows to imagine extensions on several levels. Every building block of the co-driver can be improved with further research. The introduction of higher level goals, the use of machine learning techniques to learn non-physical models (e.g. motor cortex) or adaptive techniques to fit the driver personal driving style, improving the performance of the action selection and action generation, even the jerk estimation leaves room for improvement, for instance using predictions as source of information to reformulate jerk estimation. In every case validations with a wide variety of drivers must be performed, in order to validate the architectures.

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