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Analysis of autonomous vehicle dynamics based on the big data approach

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Abstract— **This paper presents an analysis of autonomous vehicle dynamics which focuses on lateral stability. The analysis is based on the collection of big data from the signals of the vehicle. The core of the analysis method is the C4.5 machine learning algorithm. The purpose of the examinations is to determine the relationship between the various signals (e.g. yaw rate, side slip angle, longitudinal speed, adhesion coefficient) and the lateral dynamics of the vehicle. The results of the big data approach are incorporated in the stability analysis. The stability regions are calculated and used as constraints in the predictive control design of autonomous vehicles.**

I. INTRODUCTION AND MOTIVATION

The research in the field of autonomous vehicles and intelligent transportation systems has had a fast-growing tendency in the last years. Several research institutes have focused on the new challenges of autonomous vehicles, while in some cases the conventional vehicle dynamical problems are extended with new perspectives.

This transformation is illustrated through two examples. First, the purpose of driver modeling in the design of the Driver Assistance Systems (DAS) is mostly to analyze the current human conditions and intentions of the driver based on the interventions. This information has been built in the adaptation strategy of the DAS to improve the comfort or the agility of the driver [1], [2]. However, the role of driver modeling in the field of autonomous vehicles is to predict the motion of the human-driven vehicles and to design autonomous vehicle functions [3], [4], which are sufficiently ergonomic for the passengers.

The second example of the new perspectives is about the stability of vehicles. In most advanced safety systems the aim of the lateral stability analysis has been to detect the critical interventions of drivers, and the additional actuation of the vehicle systems can avoid the loss of stability in these situations [5], [6]. However, the goal of the stability analysis and limit handling in the field of autonomous vehicles is to avoid the critical situations entirely through the appropriate coordinated actuation of autonomous vehicle systems [7], [8].

This paper focuses on the last scenario, i.e., the new perspectives in the analysis of lateral stability, performances and the possibilities for their incorporation in the design of autonomous functionalities. In [9] analytical methods for the analysis of stability regions based on physical considerations have been provided. A stability bound has been defined by a phase-plane method which takes into account the vehicle side-slip angle and its angular velocity as state variables [10]. In [11] the incorporation of the stability boundaries and the operating regions of the vehicle control system are proposed. The nonlinearities of the tyre characteristics in the stability analysis are incorporated in several set-based approaches. [12] has focused on the stability regions using Lyapunov exponents, in which low order polynomials are used. Similarly, The region of attraction analysis is performed through Sum-of-Squares (SOS) method applying the polynomial approximation of tire characteristics in [13] and using the rational tire models in [14]. Moreover, the generation of controllability regions through SOS programming, in which the steering and torque vectoring control inputs are also incorporated, is found in [15]. A trajectory reversing method has also been applied for the computation of controllability sets in [16].

The literature is generally based on the physical models of the individual vehicles, and the results of control theory are applied to generate the different regions. Nowadays, the advanced technologies of automated vehicles provide a large amount of sensor data, which can be used for accurate analyses of the vehicles. The numerous measured data concerning autonomous vehicles are used for different purposes in driverless vehicles and intelligent traffic control. Big data have been used in the prediction of vehicle slip through the combination of individual measurements of the vehicle and database information [17]. Deep learning methods using the adaptive neuro-fuzzy modeling framework together with big data analysis have been applied for vehicle velocity prediction in [18]. [19] has utilized data-mining algorithms to process electric vehicle battery data for energy-consumption and driving range purposes. An optimal trajectory selection strategy focusing on the safety of the autonomous vehicles using cloud database is found in [20]. [21] has presented the idea of the path planning strategy of public vehicle systems, which uses the traffic data. Big data can also be used for safety reasons, as e.g. [22] has presented an application example to identify vehicle passenger injury factors.

This paper proposes the analysis of autonomous vehicle dynamics, focusing on lateral stability and performances. Moreover, it connects the field of vehicle performances to the data analysis approach. The contribution of the paper is the new data-driven approach and the results of the analysis, such

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as the relationship between various signals, parameters (e.g. yaw-rate, side-slip, longitudinal speed, adhesion coefficient) and the lateral dynamics of the vehicle. Moreover, the contribution is the illustration of the incorporation possibilities of the results in autonomous vehicle control. Two possibilities are presented, such as the incorporation of the decision tree in the coordination and reconfiguration strategy, and the consideration of the stability regions as constraints in the predictive control design of autonomous vehicle systems.

The contribution of the paper is in relation to the previous results of the authors on reachability and controllability, which are based on SOS programming, see e.g. [15], [23]. In those papers the impact of steering and torque vectoring interventions were examined for various vehicle control systems. Although the above mentioned high order polynomial and rational modeling of the tire characteristics provide appropriate representations of the vehicle dynamics, due to the boundaries of the modeling process, the efficiency of the model-based analysis is limited. It can result in conservativeness in the computation of controllability sets, which means that there can be several controllable states of the vehicle. The data-based analysis of the vehicle dynamic regions extends the model-based examination, while the previous results are confirmed. Thus, the data analysis can provide new possibilities and challenges in the analysis of vehicle dynamics, and this paper proposes some initial results in this field.

The structure of the paper is the following. Section II proposes the method of data collection and analysis. It also presents the core of the applied machine learning algorithm, with which the relationships are explored. The results are demonstrated in Section III through various figures. Moreover, Section IV shows the application possibilities of the data analysis results in the control design of autonomous vehicle systems. Finally, the contributions of the paper and the further challenges are summarized in Section V.

II. Method of vehicle data collection and analysis

The following section presents the method of vehicle data collection and the fundamentals of the applied machine learning algorithm for the analysis. All machine learning methods need large amount of data to train their algorithms. In this paper, the training data have been generated using the high-fidelity vehicle dynamics simulation software CarSim.

The model of the autonomous vehicle in CarSim has been controlled by a lateral tracking controller, whose inputs can be the lateral reference position and the yaw-rate. The amplitude and the frequency of these signals and the velocity of the vehicle vary during the simulations. The frequency and the amplitude are sufficiently high to reach wide ranges of states of the vehicle, such as yaw-rate, vehicle and tyre side-slips. These simulations provide stable and unstable, controllable and uncontrollable regions of the vehicle. In this way, more than ten million instances have been produced, which are the big data signals on autonomous vehicle. The classification of the instances is performed in the following way.

There is a well-known kinematic relationship between the states of the vehicle [24]:

$$\alpha_1 = \delta - \beta - \frac{l_1 \dot{\psi}}{v_x} \tag{1}$$

where α is the sideslip of the front wheels, δ is the steering angle, β is the side slip of the vehicle, l_1 is the distance between the front wheels and the vehicle center of gravity, $\dot{\psi}$ is the yaw rate in continuous time and v_x is longitudinal velocity. During the simulations all of the states are measured. The instances are classified by the percentage of the deviation which is derived from (1), such as

$$\text{if} \frac{|1+\alpha_1|}{|1+\delta-\beta-\frac{l_1\dot{\psi}}{v_x}|} \leq \varepsilon, \text{ then } i^{th} \text{ instance is controllable,}$$
$$\text{if} \frac{|1+\alpha_1|}{|1+\delta-\beta-\frac{l_1\dot{\psi}}{v_x}|} > \varepsilon, \; i^{th} \text{ instance is uncontrollable.}$$

where ε is an experimentally defined parameter.

Brief description of the C4.5 algorithm

In this paper C4.5 machine learning algorithm is used to perform the analysis on the classified data. C4.5 is a widely used machine learning algorithm, which generates decision trees for the classification of large amounts of data. The original algorithm was developed in 1960 by [25]. Over the past decades, the original method has been significantly improved, see e.g. [26], [27]. In the following the basic concept of C4.5 method is presented.

The initial step of the algorithm is the collection of data from varying instances. In general, an instance has several types of values called attributes $\mathcal{A} = \mathcal{A}_1, \mathcal{A}_2, ..., \mathcal{A}_k$. An attribute can be an independent variable or a dependent variable called class. The values of an independent variable can be continuous (numeric) or discrete (nominal). A dependent, class variable $\mathcal{C}$ is always discrete with a predefined set of values $\mathcal{C} = \mathcal{C}_1, \mathcal{C}_2 ... \mathcal{C}_m$ with m members. The collected data are divided into two parts:

1) a training set, which is used for teaching the algorithm,
2) a test set, which is used for evaluating the results.

The aim of the algorithm is to create a function ($\mathbb{F}$) based on the training set which is able to classify the instances by the selected class

$$\mathbb{F}(\mathcal{A}_1, \mathcal{A}_2 ... \mathcal{A}_k) \to \mathcal{C} \tag{3}$$

The created function is ordered into a tree structure, as illustrated in an example, see Figure 1. A tree consists of nodes and leaves. A node is associated with an attribute and a condition, and has at least two outcomes, which depend on the current value of the attribute. A leaf determines the value of the class for the current instance. The size of the resulting tree is a crucial part of the algorithm, since a large and complex tree makes it difficult to understand and use the results. Thus, C4.5 algorithm uses the greedy search method to produce the decision tree. Moreover, C4.5 algorithm considers the information gain and gain ratio criteria in the generation of the decision tree.

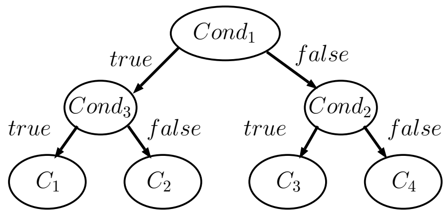


Fig. 1. Decision tree

In the method, the information content $\mathbb{I}(S)$ of a training set is determined as

$$\mathbb{I}(S) = -\sum_{j=1}^{m} \mathbb{RF} = (\mathcal{C}_j, \mathcal{S}) log(\mathbb{RF}((\mathcal{C}_j, \mathcal{S})), \tag{4}$$

where $\mathcal{S}$ is a training set that belongs to $\mathcal{C}_j$ and $\mathbb{RF}(\mathcal{C}_j, \mathcal{S})$ denotes the relative frequency of the instances. Let $\mathcal{B}$ be a test that divides $\mathcal{S}$ into subsets $\mathcal{S}_1, \mathcal{S}_2..\mathcal{S}_t$. Then the information gain $G(\mathcal{S}, B)$ is calculated in the following form:

$$\mathbb{G}(\mathcal{S}, \mathcal{B}) = \mathbb{I}(\mathcal{S}) - \sum_{i=1}^{t} \frac{|\mathcal{S}_i|}{|\mathcal{S}|} \mathbb{I}(\mathcal{S}_i) \tag{5}$$

The purpose of the gain criterion is to select the best test $\mathcal{B}$ that maximizes $\mathbb{G}(\mathcal{S}, \mathcal{B})$. However, this criterion may cause problems. The reason is that the maximization of $\mathbb{G}(\mathcal{S}, \mathcal{B})$ leads to a large number of outcomes in test $\mathcal{B}$. This can be avoided by taking into consideration the potential information $\mathbb{P}(\mathcal{S}, \mathcal{B})$, such as

$$\mathbb{P}(\mathcal{S}, \mathcal{B}) = -\sum_{i=1}^{t} \frac{|\mathcal{S}_i|}{|\mathcal{S}|} log \frac{|\mathcal{S}_i|}{|\mathcal{S}|} \tag{6}$$

The ratio of $\mathbb{G}(\mathcal{S}, \mathcal{B})$ and $\mathbb{P}(\mathcal{S}, \mathcal{B})$ must be maximized by a test $\mathcal{B}$:

$$max\left(\frac{\mathbb{G}(\mathcal{S}, \mathcal{B})}{\mathbb{P}(\mathcal{S}, \mathcal{B})}\right) \tag{7}$$

Finally, C4.5 algorithm builds up the appropriate decision tree using the optimized test $\mathcal{B}$. Further details about the generation of the decision tree are found e.g. in [26].

III. Demonstration of the analysis results

The purpose of this section is to demonstrate the reachability sets of the lateral vehicle model, which are computed through the machine learning algorithm. In the analysis the data-mining WEKA software is used, in which C4.5 algorithm has been implemented [28].

The attributes of the instances are α_1, α_2 slip at the front and rear wheels, β side slip of the vehicle, $\dot{\psi}$ yaw-rate, v_x longitudinal velocity, μ adhesion coefficient and C class. The C class has two values, i.e., *good* and *bad*, and the instances are classified by the algorithm. During the analysis the training set contains approximately 1.2 million instances, while the test set for the validation has 2 million members. In the example a mid-size passenger car is used.

The generated trees are evaluated by the cross-validation technique, the results are found in Table I. The first column in Table I shows the minimum number of instances which are contained in a leaf. The second column illustrates the percentage of the correctly classified instances. The sizes of the produced trees are in the last column. Note that the increasing number of the minimum objects decreases both the percentage of the correctly classified instances and the sizes of the trees.

TABLE I

Relationship between the tree size and the object number

Min. Objects	Correctly Classified Inst.	Size of Tree
2	99.7343%	2431
10	99.6426%	1339
100	99.2948%	315
500	98.9136%	97
1000	98.7037%	61
5000	98.1892%	17

In the following the classification with minimum 500 objects is used, because this object number has a reasonable percentage of correctly classified instances. Moreover, the generated tree is sufficiently small to be used for further analyses. In Figure 2 the instances in the test set which are classified as 'good' are illustrated. Note that the results of the decision tree appropriately cover the test set.

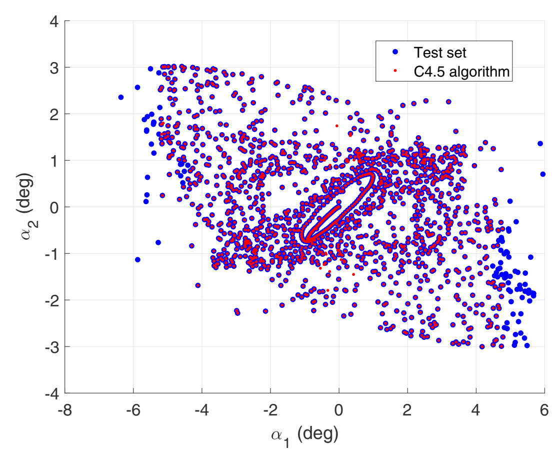


Fig. 2. Results of the decision tree

Figure 3 shows the results of the decision tree and the classified test sets in the plane of α_1 and α_2 at different velocities. The two slip attributes have high impacts on the resulting decision tree, which shows that the calculated sets fit well. Note that the sizes of the sets become larger with increasing velocity. It means that the vehicle can reach larger regions of slips at high velocities. This tendency is confirmed by the experience in vehicle dynamics.

Figure 4 illustrates the results of the classification and the test sets in the plane of yaw rate and side slip at different velocities, in which the sets also fit well. These attributes have lower impacts on the logic relations in the decision tree. The regions of reachable β and $\dot{\psi}$ increase depending

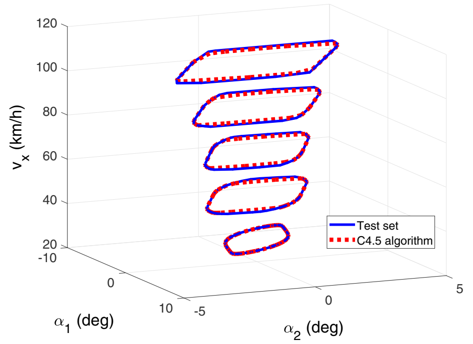


Fig. 3. α_1 and α_2 sets depending on velocity v_x

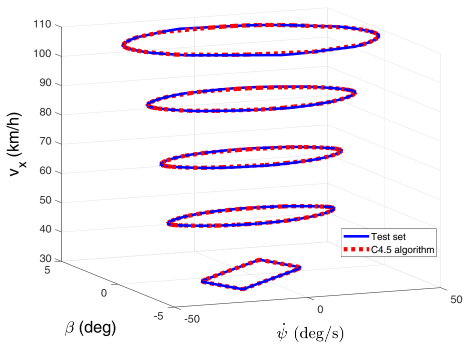


Fig. 4. $\dot{\psi}$ and β sets depending on velocity v_x

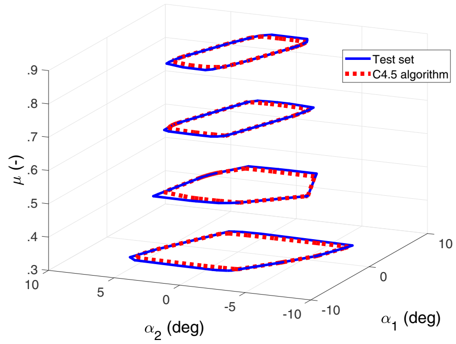


Fig. 5. α_1 and α_2 sets depending on the adhesion coefficient

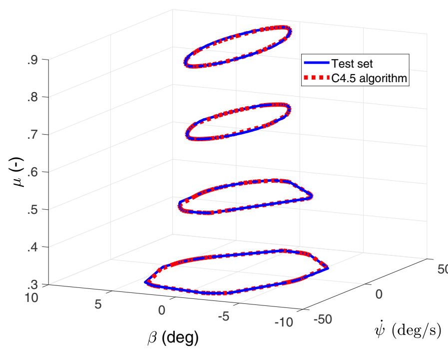


Fig. 6. $\dot{\psi}$ and β sets depending on the adhesion coefficient

on the longitudinal velocity, similarly to the tendency at the lateral slips α_1, α_2, see Figure 3.

In the following the impact of the adhesion coefficient on the reachability regions of the vehicle model is illustrated. Figure 5 shows the regions of the slips at different adhesion coefficients, in which the velocity of the vehicle is fixed at $v_x = 90\ km/h$. Note that the illustrated sets become smaller at high adhesion coefficients. The reason for this behavior is that the adhesion coefficient highly influences the lateral forces of the wheels. At high μ the small slip angle generates high lateral force, while at small μ the higher slip angle induces high lateral force.

Figure 6 shows the sets of $\dot{\psi}$ and β at different adhesion coefficients and at the fixed velocity of 90km/h. The tendency of the set sizes is similar to the previous case. The size of the sets becomes smaller at high adhesion coefficients and larger at low adhesion coefficients. The calculated sets fit to the test sets well.

IV. Incorporation of the results in autonomous vehicle control

Although the paper has proposed novel results through the examination, the goal of the analysis is their incorporation in autonomous vehicle control design. This section presents some application possibilities for analyses in the control design.

Autonomous vehicles involve several intelligent control systems. In lateral control the most effective interventions are front-rear steering, torque vectoring, differential braking and the actuation of enhanced suspension systems [5]. Since autonomous vehicles must guarantee several different performances, the coordination of the interventions has an important role in the operation of the vehicle. The results of the model-based reachability and controllability analysis have yielded exact relationships between the interventions and the vehicle dynamical parameters, see e.g. [23]. However, due to the complexity of the model-based methods the formulation of the relationships may be difficult. Thus, the contributions of the data analysis can extend the model-based results in the coordination and reconfiguration strategies of autonomous vehicle control systems. For example, the resulting decision trees can be incorporated in the logic-based algorithm of the supervisory coordination. It means that the measured and estimated signals (velocity, adhesion coefficient, side slip etc.) provide inputs for the supervisory control, whose decision concerning the coordinated actuation can be made. Through this extension the reachability and the controllability of the system can be improved.

Another application possibility of the analysis results is their incorporation in the control design of autonomous vehicle systems. Since the results provide information about the controllability regions of the vehicle system, they can be incorporated in the predictive control design. In the model-based analysis the results can be used, e.g., in the Model Predictive Control (MPC) design [6] and in the Linear Parameter-Varying (LPV) control methods [23]. Since the prediction of the vehicle motion has a high importance in the control design of autonomous vehicles, an MPC-based incorporation example is detailed below.

MPC-based application of the results

The following example presents a predictive steering control design for autonomous vehicles. The purpose of the control is to track the current path of the vehicle. It means that the minimization of the lateral error at the current moment and in the forthcoming road section must be guaranteed. It leads to a predictive tracking problem, such as

$$z(k) = y(k) - y_{ref}(k) \qquad |z(k)| \rightarrow min \quad \forall k \dots k+n \tag{8}$$

where $y(k), y_{ref}(k)$ are the lateral motion and the reference position of the vehicle, respectively, while n is the prediction horizon. The control-oriented form of the lateral vehicle dynamics is described by the bicycle model, which formulates the effects of the lateral forces and the moments on the vehicle [24]. The discrete form of the model in state-space representation is noted as

$$x(k+1) = Ax(k) + Bu(k) \tag{9}$$

where A and B are matrices, which represent the system. $x(k) = \begin{bmatrix}\omega(k) & \beta(k) & v_y(k) & y(k)\end{bmatrix}^T$ contains the states of the system, such as yaw rate $\omega(k)$ in discrete time, side-slip $\beta(k)$, lateral velocity $v_y(k)$ and lateral displacement y. $u(k)$ represents the control input, where $u(k) = \delta(k)$ and $\delta(k)$ is front wheel steering. The control input of the system is constrained by the physical limits, such as

$$u_l \leq u(k) \leq u_u \tag{10}$$

where u_l and u_u are the lower and upper bounds, respectively.

Moreover, the reachability regions, which are yielded by the data-based analysis, are incorporated in the control design to guarantee the avoidance of critical situations on the prediction horizon. The regions are inner-approximated through polygons, as illustrated in Figure 7. The states inside the approximated polygon $\mathcal{S}$ are formulated as

$$\mathcal{S} : \mathcal{S}_1 x \leq \mathcal{S}_2 \tag{11}$$

where $\mathcal{S}_1$ is an $l \times m$ matrix, l is the number of edges and m is the number of the states. Moreover, $\mathcal{S}_2$ is a vector, whose length is l.

In the problem of the MPC control it is necessary to guarantee the performance (8) on the horizon, while the states of the vehicle are inside $\mathcal{S}$ (11). The formulation of the linear MPC problem leads to a quadratic optimization through the reformulation of (8) and (9), see [29] for details. The optimization problem also contains constraints, such as state constraints from the resulting polygon $\mathcal{S}$ (11) and input constraints (10). The MPC problem is formed as

$$\min_U U^T \phi U + \beta^T U \tag{12}$$

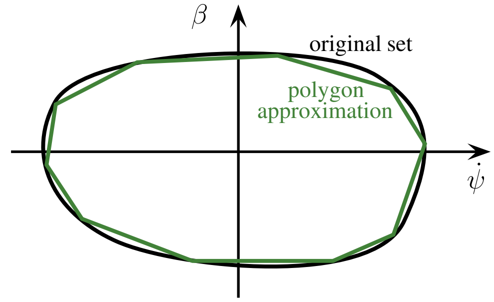


Fig. 7. Polygon inner approximation of the original set

such that

$$\mathcal{S}_1 x(i) \leq \mathcal{S}_2 \qquad \forall i = k \dots k+n \tag{13a}$$
$$u_l \leq u(i) \qquad \forall i = k \dots k+n \tag{13b}$$
$$u(i) \leq u_u \qquad \forall i = k \dots k+n \tag{13c}$$

where $U = \begin{bmatrix}u(k) & u(k+1) & \dots & u(k+n)\end{bmatrix}^T$ contains the control inputs on the horizon and ϕ, β^T are matrices. The result of the optimization is the vector U, which contains the actual and the predicted control inputs on the horizon.

In the following an illustration on the application of the data analysis results in the MPC control is presented. The simulation example is based on the set results of μ, see Figure 6. For simplicity, the adhesion coefficient is considered to be constant $\mu = 0.7$, which represents a dry concrete road. In the example a double lane change path tracking of autonomous vehicle is designed using the MPC method, which considers the state constraints formed via polygon approximation. The velocity of the vehicle is 90 km/h and 16 prediction points with $0.05s$ sampling time are considered. It results in approximately 20 m prediction on the road ahead. The states of the vehicle are the yaw rate and side-slip angle, which must be inside the polygon. Figure 8 shows that the state constraint is guaranteed, which results in small lateral errors on the route of the vehicle.

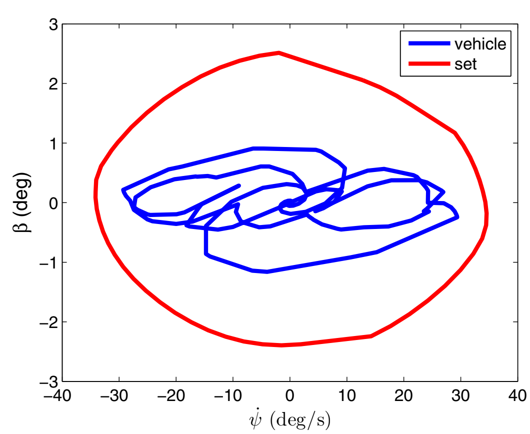
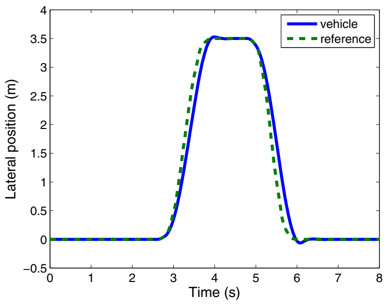
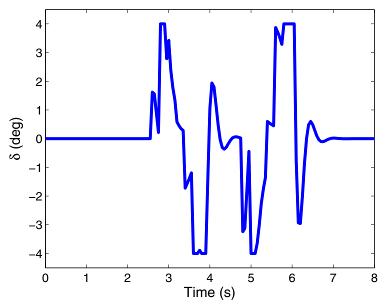


Fig. 8. State trajectory results

Figure 9(a) illustrates the path following of the vehicle, in which the tracking error is acceptable. Moreover, the steering control input of the autonomous control system is found in Figure 9(b). Through the polygon approximation the data-based analysis results are incorporated in the control design and they improve the lateral performances of autonomous vehicle.



(a) Path tracking



(b) Steering actuation

Fig. 9. Results of the double lane change simulation

V. Conclusions

The paper has proposed a data-based analysis on the dynamics of autonomous vehicles. In the analysis the big data from the signals of the vehicles have been processed through the machine learning algorithm C4.5. The paper has proposed the determination of the reachable regions of the vehicle, depending on several factors, such as the adhesion coefficients, longitudinal velocity, yaw rate and side slip. Moreover, the incorporation possibilities of the results in autonomous vehicle control have been illustrated through a simulation example.

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