Fuzzy Architecture of Safety-Relevant Vehicle Systems

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Abstract: The research discusses the problems of designing the automotive safety systems as comprehensive objects at the interface between the vehicle dynamics control and intelligent transportation systems. Taking into account the extreme uncertainty of the driving environment, the development of reliable safety control systems is possible only on the basis of intelligent analytical methods. In the work under discussion these matters are considered as applied to fuzzy sets.

Despite the existing traditions of fuzzy applications to vehicle design, the fuzzy logic has a sufficient potential for the development of advanced automotive systems, especially to ensure the driving safety. From these positions the research surveys the following issues:

- Automotive active safety and design of relevant control systems;
- Progress in fuzzy control for automotive applications using the alterable fuzzy sets;
- Integrated monitoring, identification and forecasting the road conditions on the basis of environmental parameters and vehicle dynamics;
- Design of the combined fuzzy on-board and off-board safety systems.

The main investigated topics are being illustrated with the vehicle test results as well as with the model- and hardware-in-the-loop-simulation.

Keywords: Safety; Vehicle Control; Fuzzy Sets

1. Introduction

Automotive Engineering considers two kinds of vehicle safety. The *passive* safety is a vehicle property to decrease the human injuring probability by crashes and to reduce the accident consequences. The *active* safety is a vehicle property to avoid critical situations by driving or minimize negative aftereffects by occurrence of such a situation. By a critical situation is meant a vehicle dynamic mode resulting in worsening the stability and steerability, even up to a complete loss of control, as well as in the traction or braking efficiency drop. The scope of this paper is to discuss *how the features of active safety systems* can be advanced through applications of robust computational methods on the basis of fuzzy sets.

The various devices belong to the up-to-date active safety systems, Figure 1, and they operate for the most part under uncertain conditions with many informational and energy flows. At that a universal structure of an active safety system, Figure 2, consists of a number of characteristic elements. The main logical links between them can be described as follows.

1) Parallel data channels from on *On-board sensors*, *Control Actions* of the driver and human machine interface (*HMI*) deliver information about *Actual Driving Parameters* allowing *Recognition of Vehicle Dynamics Situation* in the active safety system processor.

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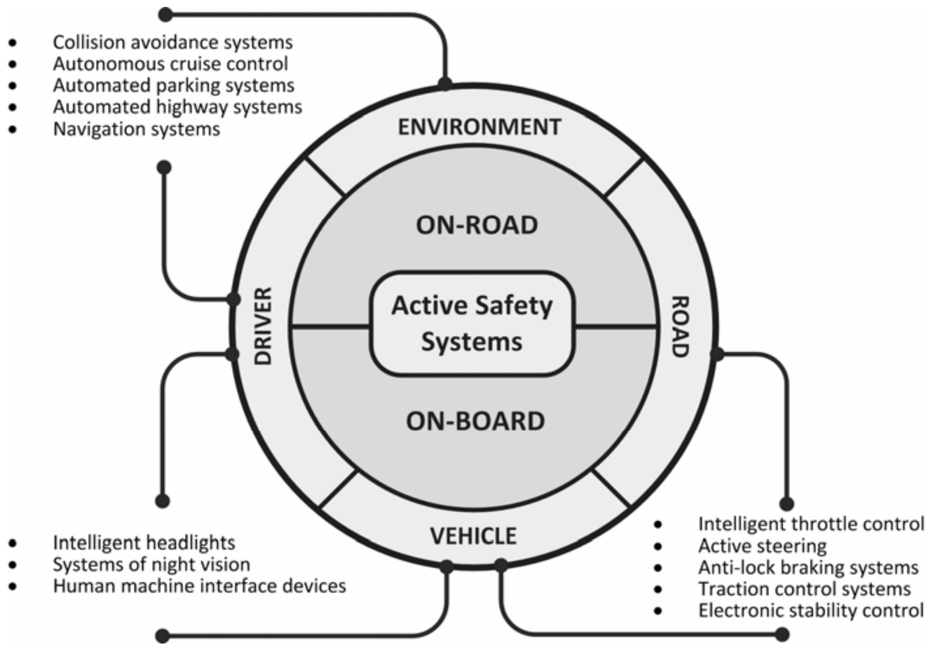

Figure 1. Family of active safety systems

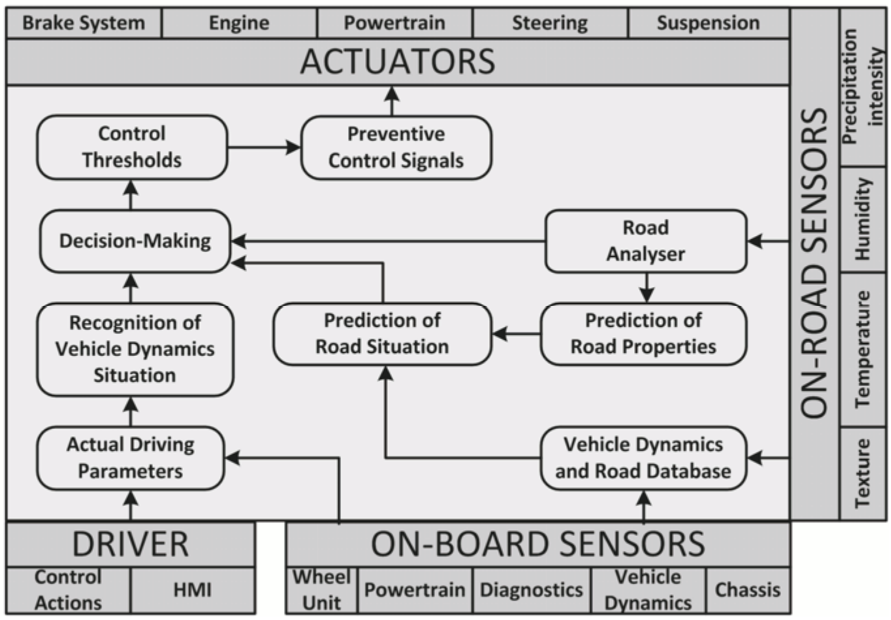

Figure 2. General structure of active safety systems

2) Additional information from *On-road sensors* makes possible the handling *Vehicle Dynamics and Road Database* and supports the operation of "*Road Analyser"* block in *Prediction of Road Properties*.

3) Informational channels from *On-board sensors* together with *Vehicle Dynamics and Road Database* allow simultaneously the *Prediction of Road Situation* in terms of vehicle dynamics parameters.

4) The *Decision-Making* block compares the predicted and recognized parameters of dynamic situation, determines the limits for the safe driving, and generates *Control Thresholds* and *Preventive Control Signals* for actuators.

5) Actuators, integrated in brakes, powertrain and other vehicle sub-systems perform necessary control actions to ensure the vehicle dynamics within the limits of safe driving.

In spite of this simplistic approach to the representation of informatio flows within an active safety system, two key problems requiring an intelligent handling can be highlighted here:

- Monitoring, identification and forecasting tire-road interaction parameters;
- Vehicle dynamics control.

Taking into account a multifaceted character of the problem, various methods of automatic control are known in active safety applications. The first systematization in this field has evolved not long ago (Kiencke and Nielsen, 2000). An analysis of diverse competitive methods makes possible an observation that fuzzy logic methods allow the creation of a unified analytical basis for most problems of active safety control, as differentiated from nonlinear principles dominating in automotive applications at the moment. Fuzzy control in the safety-related automotive systems is applied mainly to the following tasks:

- Computing the vehicle kinematic parameters (linear velocity, wheel slip, yaw rate et al.) (Buckholtz, 2002a, b; Perng, et. al., 2007; Ting, 2009);
- Controlling the brake pressure for anti-lock braking systems (Gullett, et al., 1995; Lennon, and Passino, 1999; Yazicioglu, et. al., 2008; Yu, et al., 2002);
- Control of vehicles as traffic elements, including road identification (Bauer, and Tomizuka, 1996; Bonissone, and Aggour, 2002; Wijesoma, et al., 2002; Jun, et al., 2002);
- Active suspension control (D'Amato, and Viassolo, 2000; Huang, and Chen, 2006; Yoshimura, and Hayashi, 1996);
- Vehicle driving on autonomous highways (Abdullah, et. al., 2008; Spooner, and Passino, 1997).

Although the efficiency of fuzzy control algorithms was experimentally verified by various researches and was confirmed in diverse industrial applications, the robustness of automotive fuzzy systems is the subject of much controversy as before. The present work proposes improvement of fuzzy control quality for active safety systems thanks to the application of alterable fuzzy sets. It will be shown how this approach can help in handling the numerical and linguistic uncertainty related to the vehicle dynamics. The practical realization of the developed fuzzy controllers will be illustrated by way of results of Model- and Hardware-in-the-Loop simulation on real technical objects.

2. Alterable fuzzy control and identification for automotive active safety problems

2.1. Background of Fuzzy Alteration

Fuzzy applications in the control tasks for vehicle objects are characterized by the fact that the consideration of many auxiliary parameters as input variables is often needed to improve the control quality. It can critically impact on the rule base enlargement that results in complication of fuzzy controller structure. In a marginal case it can tend to the loss of performance advantage for fuzzy control as against the conventional nonlinear control algorithms. The following example allows estimating the rule base dimension in some tasks of automotive control. The work (Hagiwara et al., 2003) argues that it is needed from 248 to 333 rules, depending on sensor system, to describe adequately the operation of car suspension through information about vertical mass acceleration. At that the vehicle model has 19 degrees of freedom (DoF). In such extreme tasks like the vehicle stability control, the object description can be complicated with the higher-order problems (Tøndel and Johansen, 2003).

Author's experience in fuzzy control algorithm synthesizing, outlined in (Ivanov et al., 2006), led to the conclusion that the robustness improvement in automotive control systems, which need instantly the computation of the tire-road friction, may be achieved by the dynamic change of membership functions taking into consideration the results of control processes. At that the DoF number for control object is invariable. The main semantic stages of proposed method can be explained using the block diagram from Figure 3. *The alteration is not identical to the encountered principle of fuzzy model development, at which the system has a database of different sets of rules bases chosen according to the current control situation. The alteration is built upon a rigid (standardized) primary rule base. There is no prior knowledge, how this base will change during the control process and will be the change at all or not. The principle of alterable fuzzy computing is further explained with a generalized algorithm.*

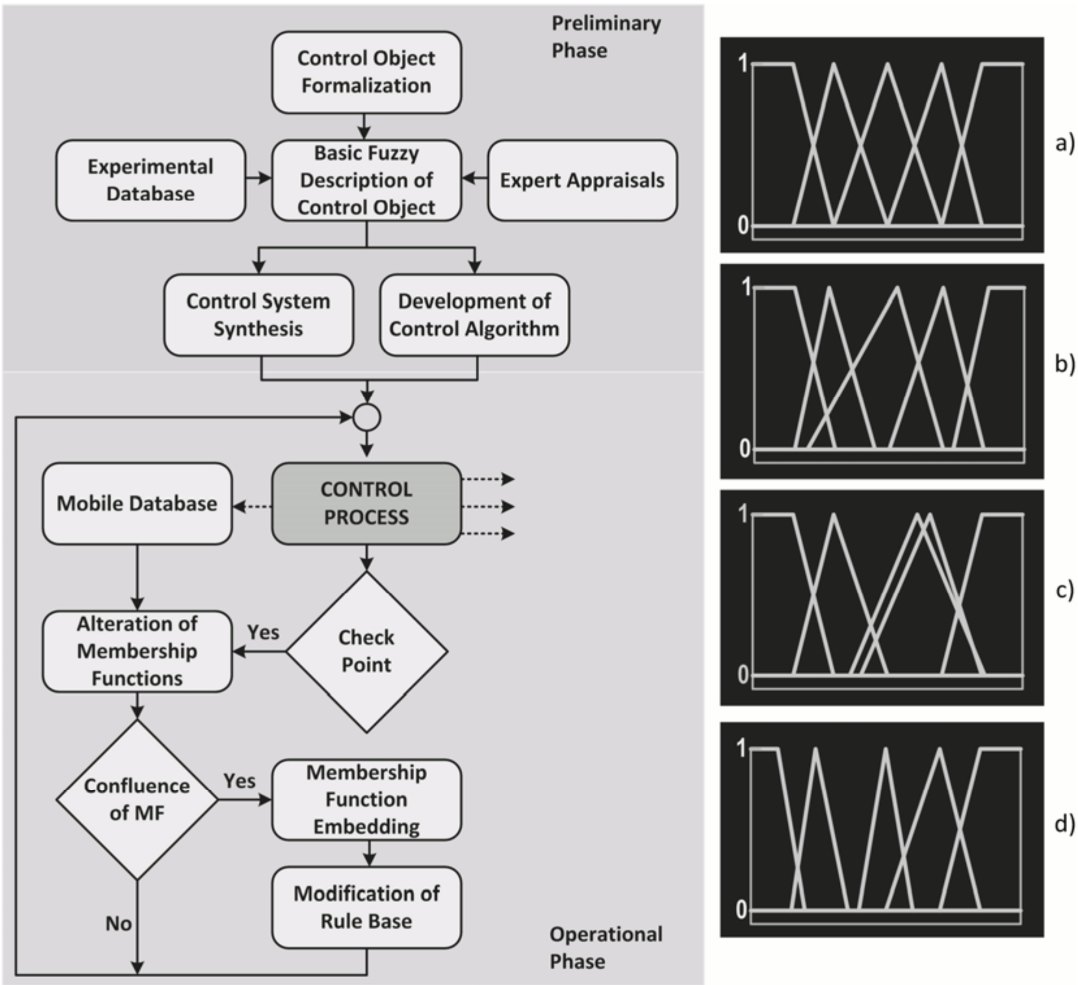

Figure 3. The block diagram of dynamic alteration of fuzzy control object

In the discussed approach all stages are divided into preliminary and operational phases. The *preliminary phase* consists of standard tasks to create a certain basic pattern of an object and to synthesize a typical *fuzzy control algorithm* for the object in hand. For this purpose, a mathematical model of the object is composed on the *formalization stage* with a view to define a minimum required and sufficient informational field for the input and output variables. It allows developing the *basic fuzzy description* of control object, where the input and output variables gain the proper membership functions and linguistic description. To clarify the next reasoning, Figure 3a gives fuzzy description for some abstract variable. As applied to examples considered below, on this stage a *database with results of the object testing* by the test bench and field conditions can be used. In specific cases the *expert appraisals* or heuristic method should be used with no wide observational data for one or another variable. Accomplishing these stages the process can pass on to the *development of control algorithm* and *control system synthesis*. As distinct from previous stages having a universal character, two current stages are strongly individual.

Disengaging from details and supposing that all previous tasks have been realized into the real-time control unit, the *operational phase* can be next considered. An important aspect is here that the results of *control process* are registered in *mobile database* indexing not only behavior of the input and output variables of control object but also the values of external factors influencing the object's operation.

At certain instant during the control process the "*Check Point*" condition is achieved. Depending on the control system preferences, this condition can be verified either after every regulation situation each or after backlog of appointed control experience for a system. The latter solution is more preferable for systems with long response time or for objects operated in more static conditions. Further the *alteration of membership functions* takes place. In doing so the system analyses the following features:

- Which of (input and/or output) variables requires the alteration of object description?
- Is it demanded to change the style of membership functions, as an example, to transform the S-shaped to bell-shaped functions etc? (The issue about additional modification of membership functions has many nuances that can entail the serious rebuilding of the overall algorithm. The presented paper does not discuss these problems.)

In the case of the alteration needed, the system generates the new description for a variable (variables), Figure 3b. In the simple case it replaces the information placed currently into a fuzzy controller.

Confluence of membership function: Two kind of objectionable cases can arise after the alteration of membership functions. There are "empty" intervals between the membership functions, Figure 3c, or large superposition of membership functions, Figure 3d.

Membership function embedding: By detecting a confluence effect, the system alters the description of the variable passes actually from the new rule base.

Modification of rule base: This stage is required after the membership function embedding.

The procedure described allows improving adaptive properties of fuzzy object control with respect to the effect of external factors, whose compensation using the conventional controller could raise the nonlinearity degree of the control system.

From the viewpoint of time factor, the *short-term*, *long-term* can be offered. The particular interest has also the *linguistic* alteration.

The *short-term* alteration is suited to the vehicle dynamics control systems. For example, it can be used to calculate the wheel slipping or to clarify the regulating curves describing the dependence of the friction from the slip.

In turn, the *long-term* alteration implies continuous monitoring for a control object. It can be the problems of off-board estimation of the friction coefficient taking into account seasonal variations in temperature, precipitation, etc. This area of tasks could be related to the Intelligent Transport Systems (ITS).

2.2. APPLICATION EXAMPLE OF ALTERABLE FUZZY PARAMETERS TO ACTIVE SAFETY SYSTEMS

Further the short-term and long-term alteration is considered as related to the fuzzy tire monitoring proposed in (Ivanov et al., 2008a; Shyrokau, and Ivanov, 2008), Figure 4.

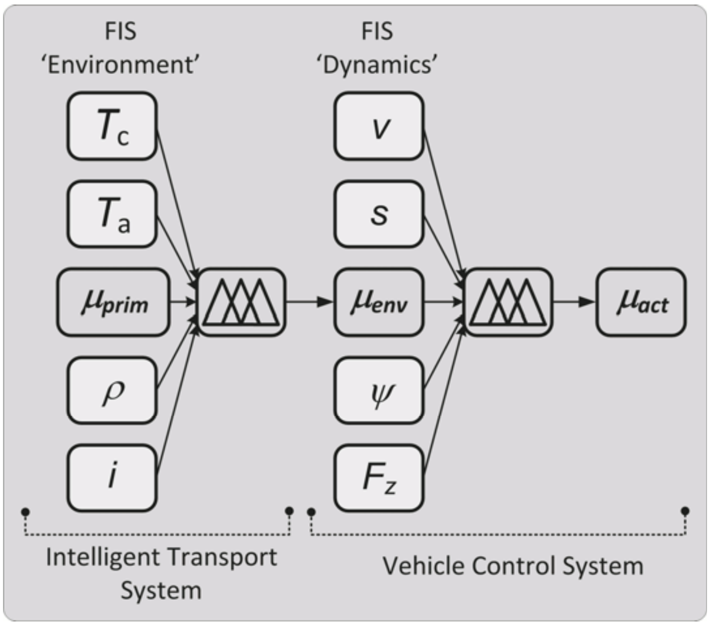

Figure 4. The block diagram of dynamic alteration of fuzzy control object
T_c - surface contact temperature; T_a - environmental temperature; ρ - environmental moisture; i - precipitation intensity (snow, rain); v - linear vehicle velocity; s- slip; ψ - yaw rate; F_z - normal wheel load; μ_{prim} - primary friction coefficient; μ_{env} - environmental friction coefficient; μ_{act} – actual friction coefficient by dynamic conditions

This architecture has been proposed to solve one of the most important tasks of active safety control: *Predict the expected maximal value of the friction coefficient for the current road surface and the current state of the environment*.

It is assumed that this characteristic is a multi-parameter function

$$\mu_{\max} = f\left(\kappa, \lambda, A, T_c, T_e, \rho, i\right) \tag{1}$$

and depends on the road surface micro- and macrotexture κ and λ, albedo A (primary value μ_{prim}) and weather conditions (environmental value μ_{env}).

The fuzzy inference system "Environment", implemented in off-board (on-road) measuring devices, deduces the tire friction coefficient μ_{env} with regard to current weather conditions. By contrast, other fuzzy inference system "Dynamics" is intended for implementation in the on-board vehicle control systems. Here the tire friction coefficient is amended in accordance with the actual vehicle dynamics parameters. The result is a new factor μ_{act}. For validating the proposed methods the Software-in-the-Loop-Modeling on the virtual proving ground for testing the automotive control systems was used with the following applications of the main software components:

- MATLAB Fuzzy Logic Toolbox: Realization of fuzzy algorithms for identification and monitoring;
- MATLAB Simulink: Control algorithms for ITS and vehicle dynamics control systems;
- AMESim: Simulation of automotive sub-systems (brakes, driveline, steering, suspension) as well as the planar vehicle dynamics.

The paper deals next with the principle of alteration for computing the parameters μ_{env} and μ_{act}. The basis for the fuzzy description of both variables lies in the Gaussian membership functions described as

$$f(\mu) = \frac{-(\mu - c)^2}{2\sigma^2}, \tag{2}$$

where σ^2 is standard deviation; c is mean value of distribution.

The fuzzy computing of the tire-road friction coefficient by environmental parameters is connected with the long-term data acquisition for observations of weather factors. In given situation the verification of the "Check Point" condition from Fig. 3 can be performed after a time interval in several tens of days. The environmental data are achieved from an ITS-application accumulating the daily information. The corresponding simulation has been performed for the certain road section, situated in the specific geographical region. The common use of environmental parameters and the primary friction coefficient μ_{prim} as input variables gives at the output the μ_{env}-value within the confidence interval of 95%.

Figure 5 displays the alteration for μ_{env}-variable. The proposed diagrams are given for the virtual testing on road fitting with the modified asphalt concrete. The initial compilation of membership functions resulted from the preliminary processing of the real roads parameters, Fig. 5a. It should be noted that "ice" is only common linguistic definition for the low friction road. It was discovered yet that a part of μ_{env}-interval keeps empty. This can be connected with the fact that the impact of water film on the maximum of friction coefficient, as compared with dry road, is less meaningful for the considered type of road (modified asphalt concrete). And vice versa, the ice-covering causes the fall of μ-value in several times. The empty interval $\mu_{env} \approx 0.25\text{-}0.50$ may fit the contaminated road. To avoid the ambiguity during operation of fuzzy controller, the membership function having the so-called linguistic description "transient road" was embedded. Figure 5b shows the μ_{env}-description for the summer conditions.

The further simulation fixed the weekly changing of input variables. Figure 5c displays the alteration of membership functions for "Check Point" in twenty weeks after the monitoring start, i.e. there are actually the winter environment conditions. Table I gives the corresponding statistical variables for the Gaussian distribution describing the membership functions.

It should be mentioned that the alteration influenced insignificantly the appearance of membership functions for μ_{env} comparing the "summer" and "winter" conditions. Nonetheless, the enlargement of interval for the "ice"-function and the narrowing for the "dry"-function has been occurred.

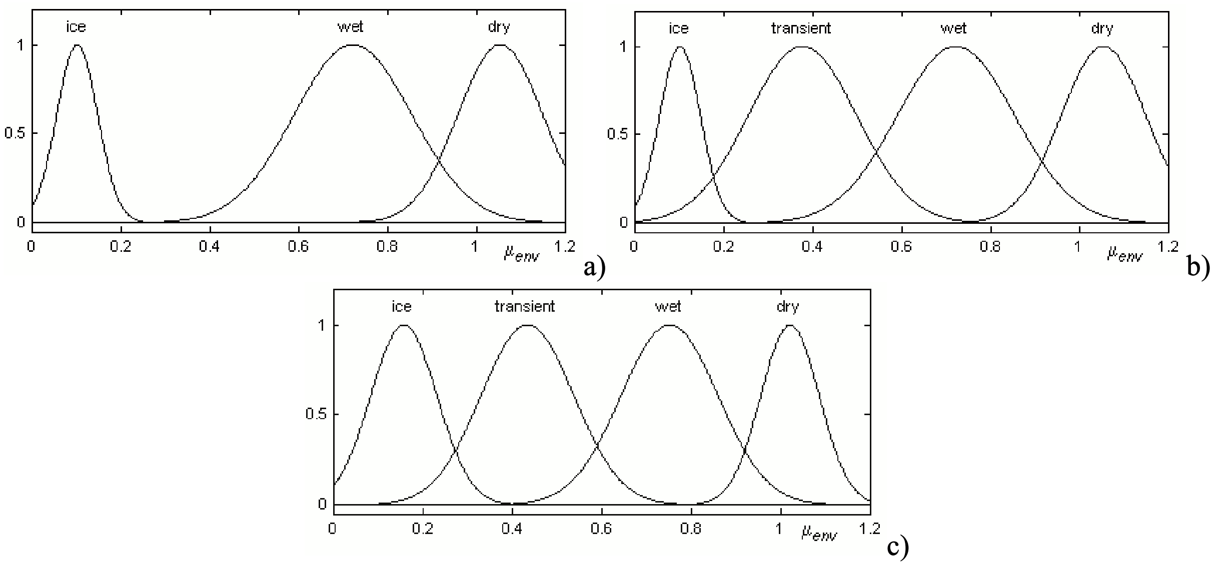

Figure 5. The membership functions for μ_{env}-variable (Shyrokau, and Ivanov, 2008)

Table I. The Gaussian distribution parameters for Fig. 5		
	Mean value c	*Standard deviation σ^2*
	Figure 5b	
Dry road	1.0547	0.0958
Wet road	0.7232	0.1327
"Transient" road	0.3780	0.1225
Ice road	0.1026	0.0462
	Figure 5c	
Dry road	1.0216	0.0654
Wet road	0.7526	0.1085
"Transient" road	0.4350	0.1040
Ice road	0.1588	0.0742

In accordance with the Fig. 4, the value of the tire friction coefficient by environmental parameters can be further transmitted to a vehicle control system to compute the tire friction coefficient μ_{act} for the actual driving situations. Analytically this parameter is the multi-parameter function of four vehicle dynamics variables at least:

$$\mu_{act} = f\left(s, v, F_z, \psi\right). \qquad (3)$$

Next simulation results, Fig. 6, are obtained for two testing objects: the car (full mass of 1500 kg) equipped with all-season tires and the heavy-duty truck (full mass of 16,000 kg). Fig. 6a displays the initial shape of membership functions for μ_{act}-variable as applied to the car. The interference of variables s, v, F_z and ψ leads to the following observations:

- The μ_{act}-value from FIS "Dynamics" is noticeably less than the friction coefficient μ_{env} by environmental conditions.
- The intervals for the dry and wet road approach each other.

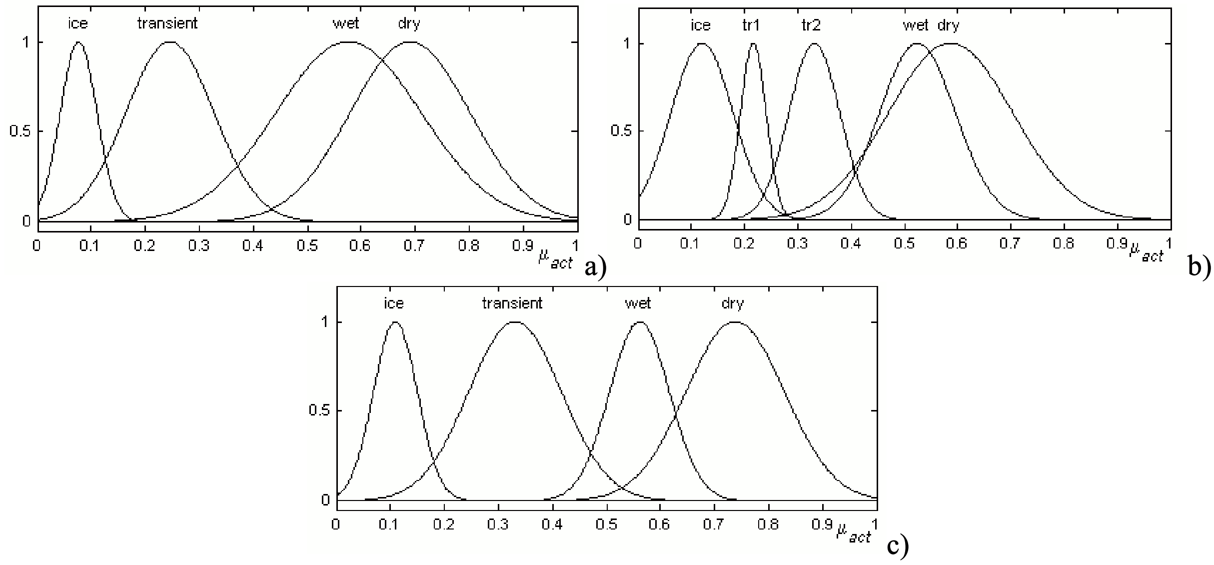

Figure 6. The membership functions for μ_{act}-variable (Shyrokau, and Ivanov, 2008)

For the most part these phenomena are caused by the hysteresis tire losses. The numerical compensation of these factors by means of a tribological model would significantly complicate the algorithm of road identification in an automotive control system.

The accumulation of virtual testing results after "Check Point" (approximately for vehicle operation by the winter conditions) discovered the confluence of membership functions for "transient" road. As a result, one new membership function has been added and the rule base of FIS "Dynamics" has been rebuilt. Figure 6b gives the corresponding description with new transient functions "tr1" and "tr2". Figure 6c gives the comparative view of membership functions related to the truck tires. Their analysis achieved the insignificant distinctions in nature of process. It should be only noted that the clear division into the dry and wet surfaces description took place at all the stages of virtual testing.

Table II illustrates the main data for Gaussian distribution for all the membership functions under discussion.

Table II. The Gaussian distribution parameters for Fig. 6

	Mean value c	*Standard deviation σ^2*
	Figure 6a	
Dry road	0.6906	0.1112
Wet road	0.5765	0.1347
Ice road	0.0767	0.0341
	Figure 6b	
Dry road	0.5868	0.1169
Wet road	0.5248	0.0716
Ice road	0.1203	0.0586
	Figure 6c	
Dry road	0.7384	0.0914
Wet road	0.5615	0.0556
Ice road	0.1094	0.0408

Hence, the chain of permanent identification of tire friction properties has been illustrated both for the ITS-related road analyzers and for automotive control systems.

The *linguistic* alteration is a subject of special consideration discussed below.

3. Handling linguistic uncertainty

3.1. Uncertainty of Tire-Surface Interaction

The essence of linguistic uncertainty for active safety applications can be explained by the example of identification of tire/road friction μ. It should be mentioned that all the next matters are discussed for the off-road vehicles.

Consider a number of statements under the assumption that they are the numerical results from tire models in automotive control system:

- A conventional control system operates with crisp statements, for example: *"Tire friction coefficient is 0.1".* This proposition can be obtained with any general tire model and it has minimal information capacity.
- The simple fuzzy statement can be as follows: *"Tire friction coefficient is around 0.1".*
- It can be derived from the simplest fuzzy model with the subsequent advance of a direct extended fuzzy proposition: *"Tire friction coefficient around 0.1 conforms to ice".* This model is more informative because there is a linguistic link between the physical magnitude of friction and road type.
- An alternative is the indirect extended fuzzy statement: *"Tire friction coefficient on ice is around 0.1".* This proposition has linguistic feedback, which allows the use of off-board physical quantities for the problems of tire dynamics. It can be, for example, the texture of the road surface or weather conditions.

The key challenge for the active safety systems is predicting possible changes in the driving environment and sequentially devising a strategy for pre-emptive vehicle control. With regard to vehicle-road interaction, the prediction activities come up against the problem of uncertainty. Within the research literature, the term "uncertainty" is used for the inherent unknown quantities present in decisions. Two kinds of uncertainty [Möller, and Beer, 2004] are present in tasks for dynamic vehicle control:

- Data uncertainty: illogical or surprising discrepancy between data and characteristics represented by data.
- Model uncertainty. This aspect relates to the representation of an object in the form of a model with certain levels of abstraction. The issue in this context is the uncertainty in the choice of model parameters and subsequent mapping.

A literature survey shows that this subject matter has been investigated most of all with regard to a number of vehicle dynamics problems:

- Construction of generic vehicle models (Brüggemann, and Kiencke, 2002; Rödönyi, and Bokor, 2005);
- Estimation of friction and slip parameters for tire-road interaction (Hansen, et al., 2005; Schmitt, et al., 2008);
- Active safety applications and driver assistance (Chen, and Ulsoy, 2001; Jansson, 2004).

It follows from the analysis of the literature and of the technological solutions realized in up-to-date control systems that the statistical instruments, especially Gaussian processes and Monte-Carlo methods, are mainly proposed to overcome the uncertainty by simulation. This approach is warranted in the case of the possible long-term observation of an object while gathering a wide range of experimental data. A different challenging topic arises when the prediction of the object's reaction to an uncertain environment is required. The presented work discusses how this matter can be handled with methods based on fuzzy sets.

Taking a view on tire friction models, it is necessary to differentiate between two kinds of vague situations.

Numerical uncertainty is applicable to the situations when the unexpected oscillations of friction value arise by the steady, unchangeable conditions of the tire rolling. For example, if the on-board tire model of a control system operates with the confidence interval μ = [0.6...0.8] for dry surface, and the computed μ–value by the vehicle driving on a homogenous, plain dry soil road leaves this interval, then the resulting uncertainty can be caused by:

- Inaccuracy of sensor-based estimation of input variables, for instance, the wheel velocities;
- Wrong choice of coefficients in the case of empirical models.

Linguistic uncertainty is a principally new problem in relation to the vehicle dynamics control. This concept is applicable to the situations, when the system recognises correctly the changing an output variable (for instance, tire friction or specific force ratio) but is not able to treat proper this information for the control algorithm. For example, the friction comes down in dynamics from 0.6 to 0.3. The uncertainty is that the value of μ = 0.3 can belong to the snow, wet pavement, sandy road or another surface. The vehicle operation on each of these grounds will be different, first of all because of unequal rolling resistance and slip properties. Therefore the linguistic information is of special importance for the intelligent control. Knowing the surface type makes possible to predict the propagation of a critical dynamic situation and perform feed-forward control actions.

The implementation both numerical values and linguistic attributes of the friction into the control algorithms is also closely connected with the proper choice of tire-surface contact models. The corresponding handling procedures with the application of fuzzy sets are discussed below. This analysis was presented in more details in (Ivanov, et. al, 2009a, b) and is related to the all-terrain vehicles.

3.2. Structure of Fuzzy System

The main propositions of fuzzy identification related to parameters of tire-surface interaction were described in the previous authors' works [Ivanov, et. al., 2008a; Ivanov, et. al., 2009a]. The advanced fuzzy strategy based on these ideas uses several variants of information flows. There are direct and indirect road parameters influencing the friction level as well as the vehicle parameters changing this friction level in accordance to the actual driving dynamics. Taking into account such an approach, the functional task of the fuzzy system under development is: *Reconstruct operational characteristics for tire dynamics control using ground- and vehicle-related parameters*.

Using this concept, the cascade architecture shown on Figure 7 can be proposed, and its key elements are further explained. The layer-specific interpretation allows a clear differentiation between the tasks of on-ground and on-vehicle estimation of tire-road parameters. The on-ground assessment of the thrust or surface friction level can be performed with the help of the off-site infrastructure as weather stations et al. As a result the estimated parameters, transmitted to the vehicle connected with the on-site devices, is further used for the purposes of on-board systems like Electronic Stability Control (ESC). The on-board controller adjusts the friction value through the vehicle parameters. The resulting output variable, particularly the tire-ground friction coefficient or specific tire contact forces, is ready for the use in vehicle dynamics algorithms

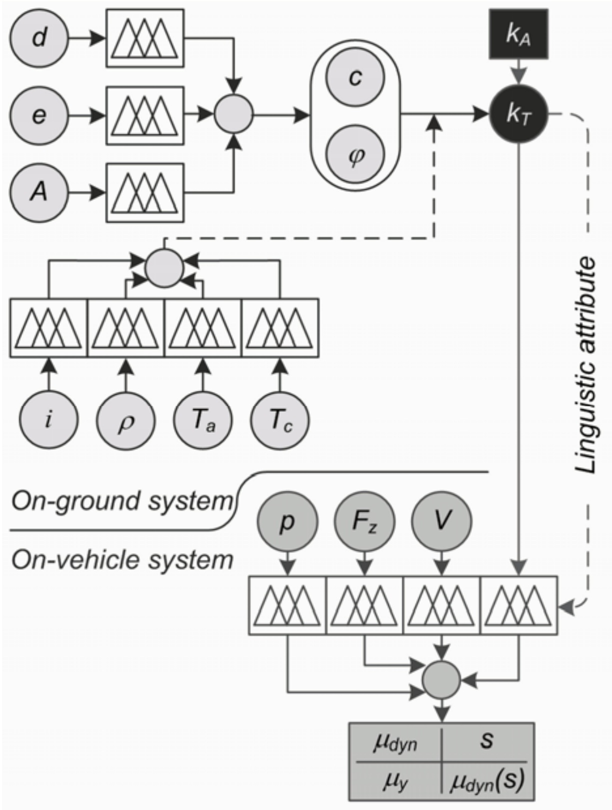

Figure 7. Structure of tire-surface interaction model for all-terrain vehicles

The first part of the identification system handles the parameters related to the wheel rolling both on the friction and cohesion surfaces. For these types of ground the Bernstein-Bekker's equation (Bekker, 1969) can be applied:

$$T = A_c \cdot c + F_z \cdot \tan\varphi . \tag{4}$$

Eq. (4) can be transformed to the dimensionless form of so-called thrust coefficient:

$$k_T = k_A \cdot c + \tan\varphi , \tag{5}$$

where k_A=A_c/F_z is the variable coefficient, which estimates the growth of the tire-ground contact area by the increase of the normal loading and depends on the tire design.

Hence the recognition of the pavement type through the thrust coefficient k_T requires the data for angle of internal friction φ and internal cohesion c at least. These parameters can be derived from the on-ground measurements of granulometry d, albedo A, and void ratio e. In addition, the values of c and φ can be corrected through environmental parameters as the ambient and contact temperature T_a and T_c, moisture ρ, and precipitation intensity i.

Next the fuzzy model seeks for the thrust coefficient k_T. The numerical result of the computing for the parameter k_T is being derived from the values of c and φ with the simultaneous correction by environmental parameters T_a, T_c, ρ, and i. The definition of linguistic attributes of the corresponding surface type is the second main task. For this purpose the approach consisting of the following procedures has been proposed:

1) The system calculates firstly the numerical k_T-value using only "featureless" linguistic attributes like numbers from "*I*" to "*IX*" on the Figure 8.

2) Considering the actual combination of environmental and pavement factors, the system generates the linguistic attribute corresponding to the expected surface type. Some most useful attributes in relation to the fuzzy description from Figure 8 are given in Table III.

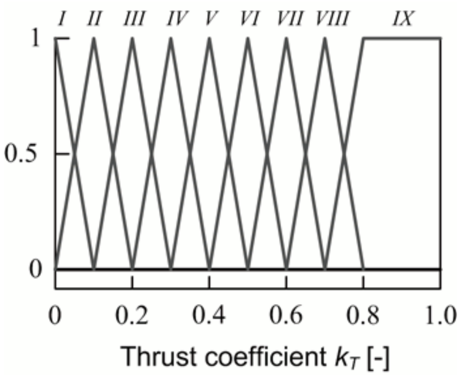

Figure 8. Proposed fuzzy description for the thrust coefficient

Table III. The variants of linguistic attributes with regard to the description from Figure 3	
I	I_a: ice
II	II_a: ice; II_b: highly wet earth soil; III_c: rolled snow
III	III_a: loose dry sand; III_b: loose snow; III_c: wet earth soil
IV	IV_a: damp gravelly sand; IV_b: dirty firm road; IV_c: loose snow
V	V_a: dry fine sand; V_b: wet clay loam
VI	VI_a: clay; VI_b: dry clay loam
VII	VII_a: sandy soils; VII_b: silty clay; VII_c: silt; VII_d: dry clay loam
VIII	VIII_a: silt; VIII_b: dense gravel soil; VIII_c: sand; VIII_d: slightly wet firm ground
IX	IX_a: dense gravel soil; IX_b: firm ground

The classification of road surfaces by linguistic attributes is of special importance for the low-friction situations, when the knowing the cause of the friction reducing can be an aid to select the right strategy for the vehicle dynamics control.

3) The derived k_T -value together with the linguistic attribute is transmitted to the on-vehicle fuzzy system to compute the actual traction (or braking) ratio

$$\mu_{dyn} = F_x / F_z \tag{6}$$

and support other necessary calculations as, for example, the reconstruction of friction–slip–curves as applied to the current terrain type.

4) The reconstruction of friction–slip–curves requires the actual information about pressure p, velocity V and normal loading F_z that can be obtained with usual on-board sensors. It should be pointed out that the fuzzy description of these variables is strongly individual for the specific vehicle.

5) The next necessary parameter for the processes of vehicle dynamics control is the wheel slip s.

6) The fuzzy inference system for the lateral force ratio μ_y can be also proposed with the input variables of p, V and F_z but the information about slip angle is required in addition.

The description of membership functions for the input and output variables, related to the on-vehicle fuzzy inference system, will not be further discussed in details because of the patent pending. Nevertheless, it should be mentioned that the purpose of the on-vehicle fuzzy inference system is to compute the actual longitudinal and lateral specific tire forces. These characteristics are crucial for the vehicle dynamics control that is discussed in the next chapter.

3.3. VEHICLE DYNAMICS CONTROL WITH FUZZY TERRAIN IDENTIFICATION

The fuzzy identification of tire-surface contact parameters can be efficient integrated into different strategies of vehicle dynamics control (VDC), for example into the Electronic Stability Control (ESC) systems. The generic structure of such a strategy, proposed for the discussed research, is given on Figure 9. It has elements of identification for the actual surface parameters to choice the control thresholds for the brake forces in the ESC system. The fuzzy procedures are also used for the parameters of yaw rate, vehicle side slip and lateral acceleration to deduce the control signal for the subsequent definition of the wheel or wheels to be controlled with additional traction or braking efforts. The detailed description of this strategy was presented in the work (Ivanov, et. al., 2009b). Further only key positions are introduced.

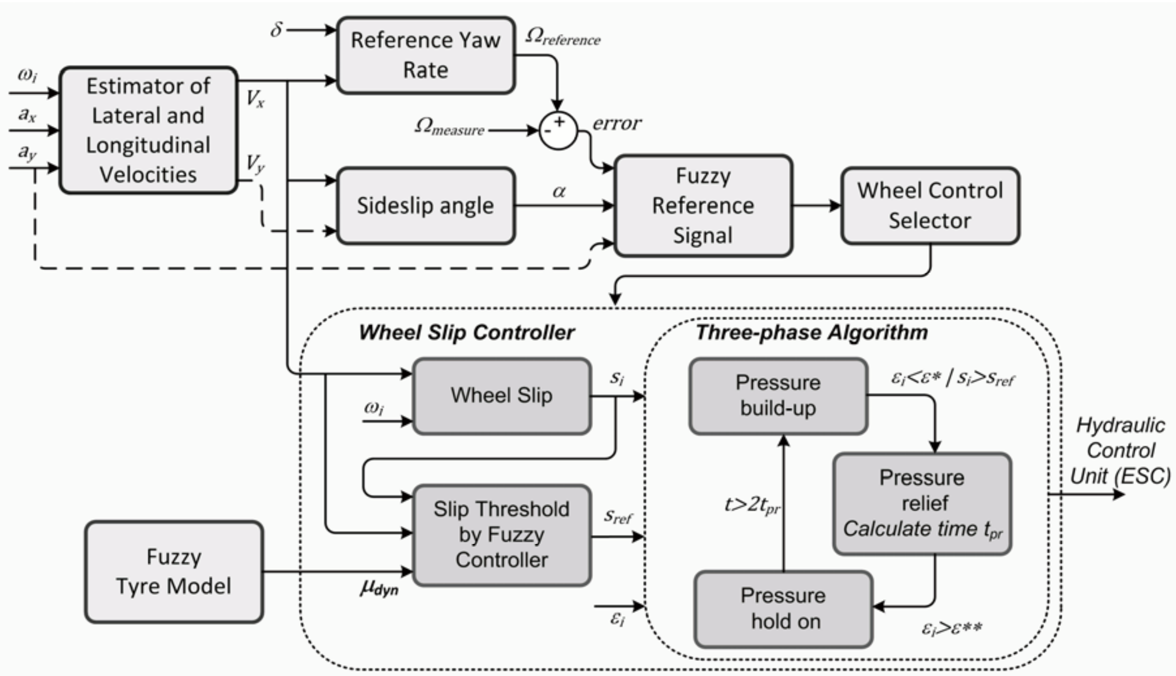

Figure 9. Structure of Vehicle Dynamics Control System

1) The VDC controller forms fuzzy reference signal on the basis of the yaw rate error, side slip, and lateral acceleration. From this signal the block ”Wheel Control Selector” identifies the wheel or wheels required the brake control effort to ensure the vehicle stability, and the rate of this effort.

2) “Wheel Slip Controller” handles the information about the required brake control efforts. The block ”Slip Threshold by Fuzzy Controller” uses the actual value of the tire-ground friction coefficient μ_{dyn} from the fuzzy tire friction model as well as the calculated wheel slips s_i to reconstruct the friction-slip curve and to find an optimal slip threshold.

3) Next the block ”Three-Phase Algorithm” determines the control signals for the hydraulic control unit of VDC system to perform the control actions on the wheel brakes.

4) As it is indicated on Figure 9, depending on relations between the reference slip s_{ref}, brake pressure hold on time t_{pr}, threshold accelerations ε^* and ε^{**}, the hydraulic control unit receives the corresponding signals for the pressure build-up, relief or hold on.

The described procedures were realised in the Hardware-in-the-Loop simulation tooling (Ivanov, et. al, 2009). The Hardware-in-the-Loop complex was used in this research work first of all to receive the real-time transient characteristic for the components of brake system and hydraulic control unit. The off-road (sport utility) light-weight vehicle was chosen as an object for the verification of composed control strategy. Its calculation scheme is shown on Figure 10, and the technical data are given in Table IV. The vehicle motion has four degrees of freedom (DOF) for planar motion and two additional rotational DOFs for wheel rotation about spin axes. This approach leads to a model with 12 DOFs.

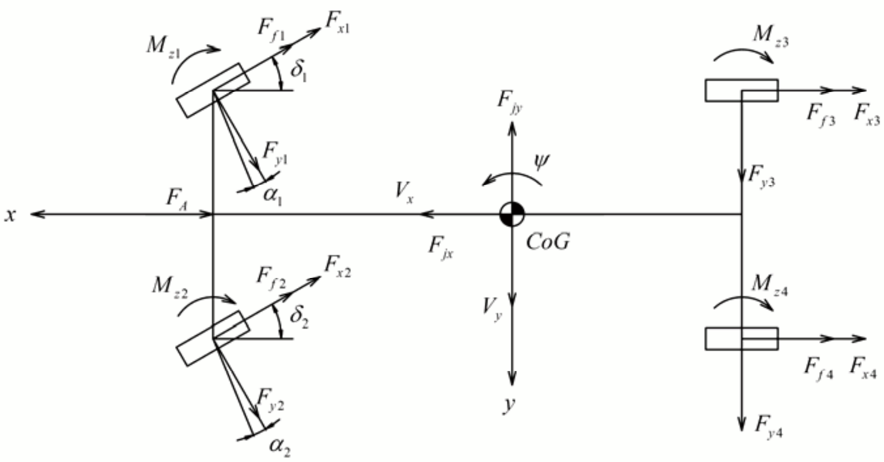

Figure 10. Vehicle model

For illustrative purposes, two most typical case studies were chosen for the vehicle dynamics control as applied to off-road mobility.

In the first case study the vehicle decelerates primarily on the firm ground with $\mu_{dyn} = 0.8$ (linguistic attribute IX_b from the Table III). Then the system detects the sharp reduction of the friction and identifies that it was caused by the loose snow (linguistic attribute IV_c from the Table III). This situation takes place after 1.5 sec of the braking start, Figure 11. It can be seen from the simulation results on Figure 11 that the controller performed the required adaptation of the control thresholds to ensure the stable braking without the dramatic wheel blocking. The sharp changing the surface conditions calls for the considerable growth of front wheels slipping. The system corrects the slip thresholds and reduces the brake pressures. The pressure reduction goes stepwise to limit the duration of the subsequent phase of pressure build-up.

Table IV. The vehicle data	
Parameter	*Value*
Vehicle gross weight, kg	2000
Sprung mass of vehicle, m_s, kg	1760
Moment of inertia along X-axis, I_x, kg·m^2	826
Moment of inertia along Z-axis, I_z, kg·m^2	3947
Vehicle base, mm	2820
Distance between the vehicle gravity centre and - front axle, mm - rear axle, mm	 1270 1550
Track, B, mm	1550
Height of centre of gravity, h, mm	760
Overall dimensions, mm	4720/1870/1830
Height of body roll centre, h_s, mm	590
Suspension roll rate, k_θ, Nm/rad	293000
Damping roll rate, c_θ, Nm/(rad·sec)	19700
Tire size	255/70 R16
Wheel rolling radius, r_w, mm	346
Moment of wheel inertia, J_w, kg·m^2	3.55
Longitudinal tire stiffness c_w, N/m	300000
Tire damping coefficient k_w, N/(m·sec)	15000
Lateral tire stiffness c_y, N/m	120000

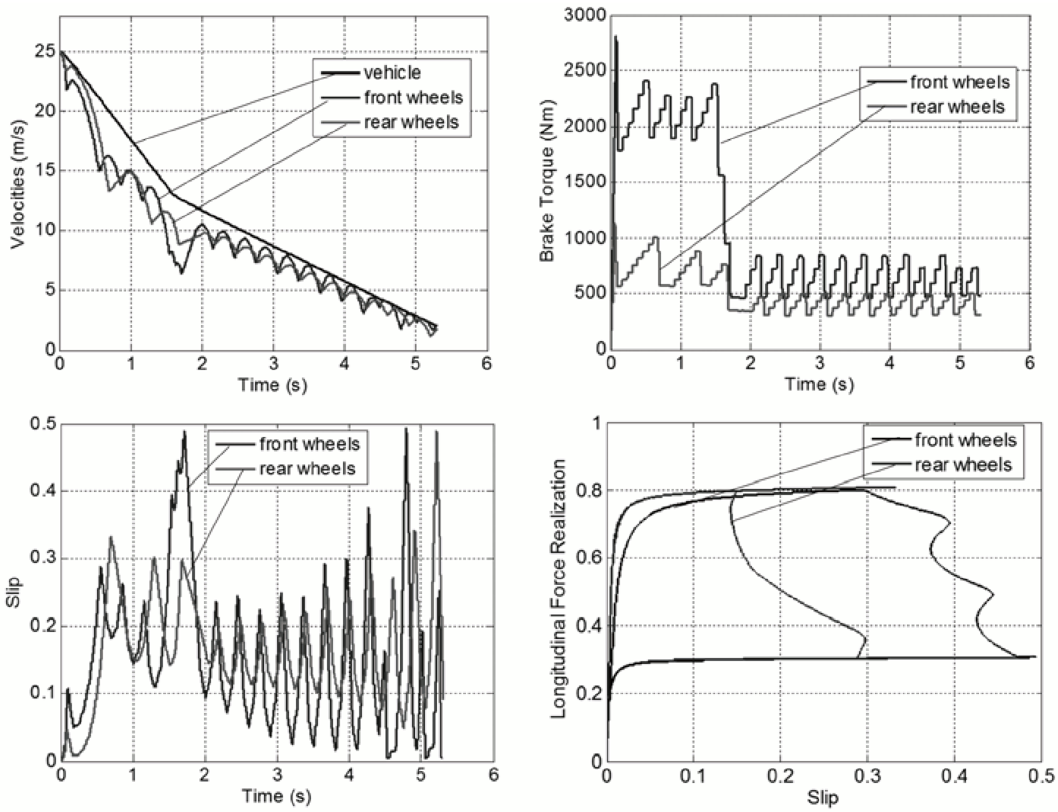

Figure 11. The simulation of the straight-line braking with the surface changing

The second case study has estimated the efficiency of the proposed control strategy for complicated lateral dynamics. Next the results of "Sine steer manoeuvre" are being considered, Figure 12. This kind of manoeuvre was proposed by the National Highway Traffic Safety Administration to compare the different vehicles by yaw dynamics (Forkenbrock, et. al., 2005).

In the case under discussion the vehicle turns on the loose snow with the sinusoidal steer manoeuvre. At that the system should be aimed at the constant turning velocity *V = 60 km/h*. It can be seen that the maximal amplitude of yaw rate has been reduced on *25%* approximately as compared to the driving without ESC system. Simultaneously the maximal amplitude of slip angle has been reduced on *81%* approximately.

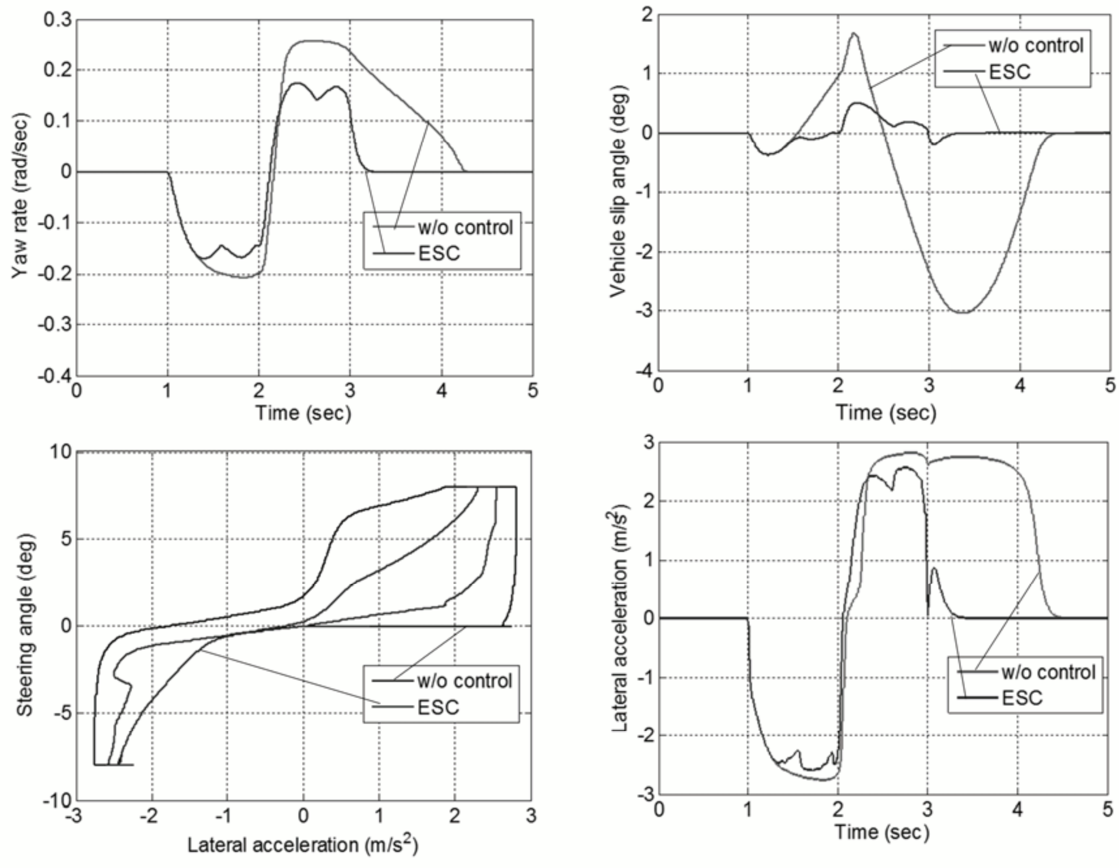

Figure 12. The simulation of the "Sine steer manoeuvre"

Conclusions

The architecture of automotive active safety systems requires the incorporation of intelligent computing methods to ensure the reliable safety control. The research results, given in the paper, demonstrate that the good opportunity in this application area can find the fuzzy sets and fuzzy control. This proposition has been illustrated with the structural variants of vehicle active safety systems demanding information about tire/surface interaction parameters. The following tasks, related to the active safety control, has been discussed in the presented work: identification of road or soil conditions, monitoring of road surface state, as well as the forecasting current road conditions via environment parameters.

The paper has also presented a new procedure to increase the robustness of fuzzy description and fuzzy control for the monitoring tire parameters and vehicle dynamics control. This approach belongs to the alteration of fuzzy sets during the control process. The advantage of this method lies in the reduction of the additional correcting input parameters and subsequent rules due to the flexible variation of a form and appointed range of membership functions.

For the architecture of active safety systems, the cascade calculation of the friction coefficient was proposed on the basis of alterable fuzzy sets with the use of the parameters of road texture, environment and vehicle dynamics. The validation results for the alterable fuzzy models have showed good effectiveness of this method, and they proved its ability to compensate the influence of external factors on the control process.

In addition, the fuzzy methods handling both the numerical and linguistic uncertainty of ground surface were described. On this base a strategy for vehicle dynamics control was proposed as applied to all-terrain vehicles. Its practical application was illustrated with the results of Hardware-in-the-Loop-simulation. The case studies for the straight-line braking and Sine steer manoeuvre have confirmed the good functionality of vehicle dynamics control strategies on the basis of fuzzy assessment of surface properties.

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References

Abdullah, R., Hussain, A., Warwick, K., and Zayed, A. Autonomous Intelligent Cruise Control Using a Novel Multiple-Controller Framework Incorporating Fuzzy-Logic-Based Switching and Tuning, *Neurocomputing,* 71(13-15), pp. 2727-2741, 2008.

Bauer, M. and M. Tomizuka. Fuzzy Logic Traction Controllers and their Effect on Longitudinal Vehicle Platoon System. *Vehicle Systems Dynamics*, 25(4): 277-303, 1996.

Bekker, M. G. *Introduction to Terrain-Vehicle Systems,* Ann Arbor: University of Michigan Press, 846 p., 1969.

Bonissone, P., and Aggour K. Fuzzy Automated Braking System for Collision prevention, *General Electric Company – Technical Information Series*, 2002GRC188, 11 pp., 2002.

Brüggemann, H., and Kiencke, U. Uncertainty Theory in Vehicle Dynamics Simulation, *Proc. of the American Control Conference at Anchorage, USA, May 8-10, 2002*, pp. 298-303, 2002.

Buckholtz, K.R. Use of Fuzzy Logic in Wheel Slip Assignment – Part II: Yaw Rate Control with Sideslip Angle Limitation, *SAE Technical Paper Series*, paper No. 2002-01-1220, 2002.

Buckholtz, K.R. Use of Fuzzy Logic in Wheel Slip Assignment – Part I: Yaw Rate Control, *SAE Technical Paper Series*, paper No. 2002-01-1221, 2002.

Chen, L.-K., and Ulsoy, A.G. Identification of a Driver Steering Model, and Model Uncertainty, from Driving Simulator Data, *Journal of Dynamics Systems, Measurement, and Control*, 123: 621-629, 2001.

D’Amato, F.J., and Viassolo, D.E. Fuzzy control for active suspensions, *Mechatronics*, 10(8): 897-920, 2000.

Forkenbrock, G.J., Elsasser, D. and B. O’Harra. NHTSA's Light Vehicle Handling and ESC Effectiveness Research Program, *Proc. of 19th International Technical Conference on the Enhanced Safety of Vehicles*, Washington, D.C., June 6-9, 2005, paper 05-0221, 16 pp.

Gullett, Ch. et al. 'Intel Fuzzy Logic Tool Simplifies ABS Design, *Intel Corporation Application Note*, No. 272595–001, 8 pp., 1995.

Hagiwara, T., Panfilov, S.A., Uljanov, S.V., Takahashi, K. and Diamante, O. An Application of a Smart Control Suspension System for a Passenger Car Based on Soft Computing, *Yamaha Motor Technical Review*, 2003.01.15, 10 pp., 2003.

Hansen, J., Murray-Smith, R. and Johansen, T.A. Nonparametric Identification of Linearizations and Uncertainty Using Gaussian Process Models – Application to Robust Wheel Slip Control, *Proc. of 44th IEEE Conf. of Decision and Control, and the European Control Conf. at Seville, Spain, December 12-15, 2005*, pp. 5083-5088, 2005.

Huang, S.-J., and Chen, H.-Y. Adaptive Sliding Controller with Self-Tuning Fuzzy Compensation for Vehicle Suspension Control, *Mechatronics,* 16(10), pp. 607-622, 2006.

Ivanov, V. Investigation into Tyre-Road Interaction Based on Fuzzy Logic Methods. *International Journal of Vehicle Autonomous Systems*, 3(2/3/4): 198-215, 2005.

Ivanov, V., Algin, V. and Shyrokau, B. Intelligent Control for ABS Application with Identification of Road and Environmental Properties, *International Journal of Vehicle Autonomous System*, 4(1): 44-67, 2006.

Ivanov, V., Augsburg, K. and Shyrokau, B. Alterable Fuzzy Computing for Monitoring Tire Parameters, *Proc. of AVEC'08 / International Symposium on Advanced Vehicle Control at Kobe, Japan*, 2008.

Ivanov, V., Shyrokau, B. and K. Augsburg. Application of Uncertain Tyre Parameters to Intelligent Vehicle Control, *Proc. of 11th European Regional Conference of the International Society for Terrain-Vehicle Systems,* 2009.

Ivanov, V, Shyrokau, B. and K. Augsburg. Handling Tyre Parameters by Uncertain Conditions, *Proc. of 21st IAVSD Symposium, Stockholm*, paper P118, 2009.

Ivanov, V., Shyrokau, B., Augsburg, K. and V. Algin. Identification and prediction of Tyre-Surface Interaction Parameters*, Proc. of 16th International Conference of ISTVS*, 2008.

Jansson, J. Dealing with Uncertainty in Automotive Collision Avoidance, In: *Advanced Microsystems for Automotive Applications*, Ed.: J. Valldorf and W. Gessner, Springer, Berlin-Heidelberg, pp. 165-180, 2004.

Jun, L., Jianwu, Z., and Fan, Y. An Investigation into Fuzzy Control for Anti-lock Braking System Based on Road Autonomous Identification, *SAE Technical Paper Series*, paper No. 2001-01-0599, 2001.

Kiencke, U. and Nielsen, L. *Automotive Control Systems*. Springer, Heidelberg, 2000.

Lennon, W.K., and Passino, K.M. Intelligent Control for Brake Systems, *IEEE Transactions on Control Systems Technology*, 7(2): 188–202, 1999.

Möller, B. and Beer, M. *Fuzzy Randomness: Uncertainty in Civil Engineering and Computational Mechanics*, Springer, Berlin-Heidelberg, 2004.

Perng, J.-W., Wu, B.-W., Liao, T.-Y., and Lee, T.-T. Robust Stability Analysis of a Fuzzy Vehicle Lateral Control System Using Describing Function Method, In: *Advances in Soft Computing*, Vol. 41, pp. 769-779, 2007.

Rödönyi, G., and Bokor, J. Uncertainty Identification for a Nonlinear LPV Vehicle Model Based on Experimental Data, *Proc. of 44th IEEE Conf. of Decision and Control, and the European Control Conf. at Seville, Spain, December 12-15, 2005*, pp. 2682-2687, 2005.

Schmitt, K., Madsen, J., Anitescu, M., and Negrut, D. A Gaussian Process Based Approach for Handling Uncertainty in Vehicle Dynamics Simulation, *Proc. of IMECE 2008 Congress at Boston, USA, November 2-6, 2008*, paper IMECE2008-66664, 11 p., 2008.

Shyrokau, B. and Ivanov., V. Alterable Fuzzy Sets in Automotive Control Applications. *International Journal of Modelling, Identification and Control*, 3(3): 305-317, 2008.

Spooner, J.T., and Passino, K.M. Fault–Tolerant Control for Automated Highway Systems, *IEEE Transactions on Vehicular Technology*, 46(3): 770–785, 1997.

Ting, C.-S. An Output-Feedback Fuzzy Approach to Guaranteed Cost Control of Vehicle Lateral Motion, *Mechatronics,*19(3), pp. 304-312, 2009.

Tøndel, P., and Johansen, T.A. Lateral Vehicle Stabilization Using Constrained Nonlinear Control, *Proc. of European Control Conference ECC'2003*, 2003.

Wijesoma, W.S., Kodagoda, K.R.S. and Teoh, E.K. Stable Fuzzy State Space Controller for Lateral Control of an AGV, *Journal of VLSI Signal Processing*, 32: 189-201, 2002.

Yazicioglu, Y., and Unlusoy, Y. S. A Fuzzy Logic Controlled Anti-lock Braking System (ABS) for Improved Braking Performance and directional stability, *International Journal of Vehicle Design*, 48(3/4), pp. 299 – 315, 2008.

Yoshimura, T., and Hayashi, N. Active Control for the Suspension of Large–sized Buses Using Fuzzy Logic, *International Journal of Systems Science*, 27(12): 1243–1250, 1996.

Yu, F., Feng, J.–Z., and Li, J. 'A Fuzzy Logic Controller Design for Vehicle ABS with a On–line Optimized Target Wheel Slip Ratio, *International Journal of Automotive Technology*, 3(4): 165–170, 2002.