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Intelligent Identification of Vehicle Dynamics based on Local Model Network

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Abstract
In this paper, I propose an intelligent approach for the dynamic identification of vehicles. The developed approach is based upon data-driven identification and uses a high performance local model network (LMN) for estimation of the vehicle longitudinal velocity, lateral acceleration, and yaw rate. The proposed LMN requires no pre-defined standard vehicle model, and uses measurement data to identify vehicle dynamics. LMN is trained by the hierarchical binary tree learning algorithm, which results in a network with maximum generalizability and the best linear or non-linear structure. The proposed approach is applied to a measurement dataset obtained from a Volvo V70 vehicle in order to estimate its longitudinal velocity, lateral acceleration, and yaw rate. The identification results reveal that LMN can identify accurately the vehicle dynamics. Furthermore, comparison of the LMN results and a multi-layer perceptron neural network demonstrates the far better performance of the proposed approach.

Keywords: *Local Model Network, Hierarchical Binary Tree, Vehicle Dynamics, Identification, Neural Network.*

1. Introduction
Dynamic modeling of vehicles provides a mathematical description of vehicle dynamics in different operating conditions, which can be used for simulation and control of vehicles. Many advanced functions of today's vehicles such as electronic stability programs (ESPs), tire pressure monitoring systems (TMSs), and road-tire friction measurement system require a valid dynamic model of the vehicle. Hence, an accurate modeling of the vehicle is important [1]. However, such a modeling task is challenging and complicated, and requires sophisticated modeling approaches.

Generally, two different approaches can be identified for dynamic modeling of vehicles, i.e. analytical modeling and data-driven identification. Analytical modeling, which is based upon the physical laws governing the vehicle, requires many details [2-3]. Consideration of different operating regimes of the vehicle complicates analytical modeling, imposing a huge computational burden on the modeling process. Simplifying assumptions are not a good solution in these circumstances as they may lead to invalid and inaccurate vehicle model.

The data-driven identification techniques such as non-linear auto-regressive models with exogenous variables (NARX) [4], neural networks [5], and neuro-fuzzy models [6, 7] are able to model the dynamics of complex non-linear systems, e.g. vehicles using a set of input-output measurements. They usually require no pre-specified assumption about the system or process to be identified. This property makes data-driven approaches a suitable solution when dealing with complicated systems with a large number of influential variables.

Various attempts have been made to identify a dynamic vehicle model using the measurement data. For instance, Macek et al. have applied dynamic modeling and parameter identification for autonomous navigation of vehicles [8]. The prediction error technique has been used in [9] for dynamic identification of vehicles. Moreover, artificial neural network (ANN)-based approaches have been designed to identify vehicle dynamics [10, 11].

Among the various identification techniques, local modeling approaches (LMAs) have gained popularity over the past decade, owing to their ability in identification and control of highly non-linear and complex systems through local description of different operating regimes of the system by different local models (LMs). In addition, they are able to integrate the structured knowledge about the system, and hence, provide a gray-box modeling outcome [12, 13]. LMAs bear different names such as local model networks (LMNs) [14], Takagi-Sugeno (TS) fuzzy models [15], piecewise linear models [16], and local regression [17].

In this work, we developed a local model network for dynamic modeling and identification of vehicles. The proposed LMN is made up of a number of local linear models (LLMs), each one of which describes a certain operating region of the vehicle. Interestingly, using LLMs allows a good trade-off between the required number of the local models and their complexity, and more interestingly, provides the possibility of transferring parts of the mature field of linear control theory to the non-linear world. The proposed LMN will be used to model a dynamic system such as the longitudinal velocity, lateral acceleration, and yaw rate of a Volvo v70 vehicle using three input variables of slip of front right tire (SFRT), slip of front left tire (SFLT), and steering angle.

The rest of this paper is organized as what follows. The structure of the proposed LMN and its learning algorithm are presented in Section 2. The procedure of dynamic vehicle identification is explained in Section 3. In Section 4, I report the results of identification of a Volvo v70 vehicle using LMN and provide some comparisons to several other approaches. Finally, the paper is concluded in Section 5.

2. Local model networks

Local modeling approaches (LMAs) are powerful techniques for identification and prediction of complex non-linear processes and systems. They are able to integrate the structured knowledge about the process, facilitating the procedure of complex system identification [13]. The ability to describe different operating regimes of a system or process by different local models (LMs) is considered a promising property of LMAs. As a favorable class of LMAs, local model network (LMN) models are fuzzy inference systems that can use neural network learning algorithms for estimation of their structures and parameters [15]. They are composed of a number of arbitrary LMs (allowed to be linear, non-linear, etc.) weighted by their corresponding validity functions, as shown in figure 1. In this paper, an LMN composed of local linear models (LLMs) is employed for the identification of vehicle dynamics. LLMs provide a good trade-off between the required number of the local models and their complexity, and more interestingly, they offer the possibilities of transferring parts of the mature field of linear control theory to the non-linear world [15]. The hierarchical binary tree (HBT) learning algorithm [13] is also employed to determine the structure of LMN and estimate its parameters.

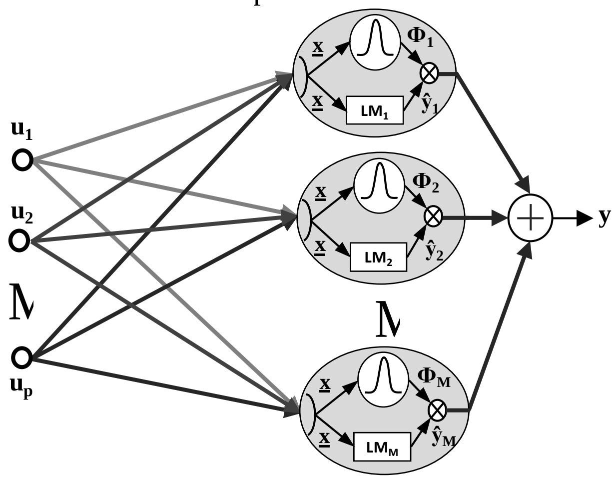

Figure 1. Structure of LMN with *p* inputs and *M* local models.

2.1. Model structure

In general, an LMN includes several LMs weighted by their corresponding validity functions. The general mathematical expression of an LMN with *p* inputs, $\underline{u}=[u_1,u_2,\ldots,u_p]^{tr}$, and *M* local models as illustrated in figure 1, is given by:

$$\hat{y}=\sum_{i=1}^{M} f_i\left(\underline{u}\right)\Phi_i\left(\underline{u}\right) \tag{1}$$

where, $f_i(\cdot)$ is an arbitrary function describing the *i*-th local model (LM_i), Φ_i indicates the corresponding validity function of LM_i, and $\hat{y}$ denotes the LMN output. The validity functions may be interpreted as the operating point-dependent weighting factors, which determine the contribution of their associated LMs to the final output. Moreover, each local model and its validity function together realize a non-linear neuron. It can also be demonstrated that LMN in (1) is equivalent to a fuzzy inference system with M rules, where $\Phi_i(\underline{u})$ and $h_i(\underline{u})$ represent the rule premises and associated rule consequents, respectively [15].

The following two restrictions are imposed on the validity function to allow for (1) a smooth transition between the local models and (2) a reasonable interpretation of them.

- The validity functions are smooth and take their values between 0 and 1.
- The validity functions must form a partition of unity; i.e. $\sum_{i=1}^{M} \Phi_i\left(\underline{u}\right)=1$.

As stated earlier, use of LLMs in the structure of a LMN provides a good trade-off between the required number of the local models and their complexity as well as the possibility of transferring parts of the mature field of the linear control theory to the non-linear world. If f_i in (1) is chosen as LLMs, then:

$$f_i\left(\underline{u}\right)=\theta_{i,0}+\theta_{i,1}u_1+\ldots+\theta_{i,p}u_p \tag{2}$$

where, $\theta_{i,0}\ \theta_{i,1} \ldots \theta_{i,p}$ are the parameters of LLM$_i$, also called the linear parameters of LMN. In order to estimate these linear parameters, the local error of the corresponding LLM is minimized for the available training data:

$$\min_{\underline{\theta}_i}\left\{I_i=\sum_{j=1}^{N}\Phi_i\left(\underline{u}\left(j\right)\right)e\left(j\right)\right\}, i=1,\ldots,M \tag{3}$$

where, $e(j) = y(j) – \hat{y}(j)$ and $\underline{y} = [y(1), \ldots, y(N)]$ are N target outputs. The weighted least square (WLS) solution of (3) leads to:

$$\underline{\theta}_i=\left(\underline{R}_i^T\underline{D}_i\underline{R}_i\right)^{-1}\underline{R}_i^T\underline{D}_i\underline{y} \tag{4}$$

where, $\underline{R}_i$ is the regression matrix associated with the i-th local model for the N training samples:

$$\underline{R}_i=\begin{bmatrix} 1\ u_1(1) & u_2(1) & \ldots & u_p(1) \\ 1\ u_1(2) & u_2(2) & \ldots & u_p(2) \\ \vdots\ \vdots & \vdots & & \vdots \\ 1\ u_1(N) & u_2(N) & \ldots & u_p(N) \end{bmatrix}_{N\times n_p} \tag{5}$$

and the $N\times N$ diagonal weighting matrix, $\underline{D}_i$, is given by:

$$\underline{D}_i=\begin{bmatrix} \Phi_i\left(\underline{u}(1)\right) & 0 & \ldots & 0 \\ 0 & \Phi_i\left(\underline{u}(2)\right) & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \ldots & \Phi_i\left(\underline{u}(N)\right) \end{bmatrix} \tag{6}$$

2.2. Identification of model structure

In order to fully identify the structure of an LMN, the number of non-linear neurons and parameters of the validity functions must be determined in addition to the LLMs' parameters. This is done by the hierarchical binary tree learning algorithm, which is a heuristic tree-construction algorithm and hierarchically partitions the input space into the hyper-rectangular sub-domains through axis-orthogonal splits. In each iteration of the algorithm, the worst-performing local model is divided into two halves. Therefore, two new local models are generated and their associated validity functions are determined. This procedure continues until the desirable performance is achieved [13].

Figure 2 shows the architecture of the HBT algorithm by a hierarchical binary tree example. In this architecture, each node i corresponds to the partition of the input space into two areas by the splitting function $\psi_i(\underline{\tilde{x}})$ and its counterpart $1-\psi_i(\underline{\tilde{x}})$. Interestingly, the two splitting functions automatically sum up to unity; therefore, no normalization is required and its undesirable side-effects such as reactivation in LOLIMOT are avoided.

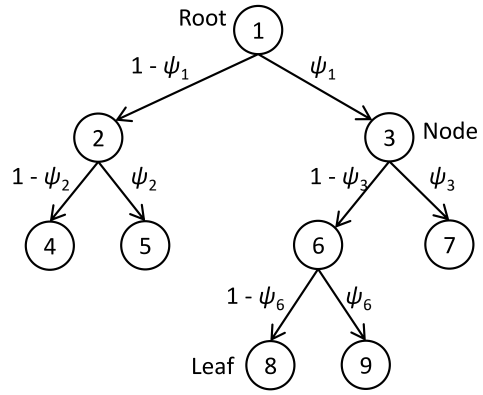

Figure 2. Hierarchical model structure with 5 local models (at leaves).

The partitioned regions are further sub-divided by the succeeding nodes, if any, and the binary tree ends with a set of end nodes, called leaves. Each leaf represents a local model and its contribution to the overall model output is given by its validity function, computed by multiplication of all splitting functions from the root of the tree to the corresponding leaf. For the binary tree in figure 2 with nine nodes and five leaves, the validity functions can be expressed as:

$$\Phi_4\left(\underline{u}\right)=\left(1-\psi_2\left(\underline{u}\right)\right)\left(1-\psi_1\left(\underline{u}\right)\right) \tag{7}$$

$$\Phi_5\left(\underline{u}\right)=\left(\psi_2\left(\underline{u}\right)\right)\left(1-\psi_1\left(\underline{u}\right)\right) \tag{8}$$

$$\Phi_7\left(\underline{u}\right)=\psi_3\left(\underline{u}\right)\psi_1\left(\underline{u}\right) \tag{9}$$

$$\Phi_8\left(\underline{u}\right)=\left(1-\psi_6\left(\underline{u}\right)\right)\left(1-\psi_3\left(\underline{u}\right)\right)\psi_1\left(\underline{u}\right) \tag{10}$$

$$\Phi_9\left(\underline{u}\right)=\psi_6\left(\underline{u}\right)\left(1-\psi_3\left(\underline{u}\right)\right)\psi_1\left(\underline{u}\right) \tag{11}$$

It is simply verified that:

$$\sum_{i=\{4,5,7,8,9\}}\Phi_i\left(\underline{u}\right)=1 \tag{12}$$

The general form of a splitting function is expressed below:

$$\psi_i\left(\underline{u}\right)=\frac{1}{1+e^{-s_i\left(d_{i,0}+d_{i,1}u_1+\dots+d_{i,p}u_p\right)}} \qquad (13)$$

which is a sigmoid function with the direction vector $\underline{d}_i$ = $[d_{i,1}\ \dots\ d_{i,p}]^T$ deciding the direction of split and the position parameter $d_{i,0}$, specifying the position of the split and the smoothness parameter s_i setting the smoothness of the split.

The unknown parameters of the sigmoid functions are determined by the HBT algorithm, summarized below.

I. Start with the initial model: set M = 1, start with a single LM whose validity function ($\Phi_1(\underline{\tilde{x}}) = 1$) covers the whole input space and estimates the model parameters using (4).

II. Find the worst LM: calculate a loss function defined by (7) for each of LM_i, i = 1, …, M, and find the worst-performing local model (LLM_{wt}).

III. Check all divisions: the validity region of LLM_{wt} must be divided into two equal hyper-rectangles (two new validity regions) in all p dimensions.

III (a). Construct the splitting functions: for each *p* division, a splitting function must be determined. The positioning parameter $w_{i,0}$ is set equal to the center of the LLM_{wt} at the split dimension, all entries of the direction vector except the one that corresponds to the division dimension are zero, and the smoothness parameter is simply set proportional to the length of the newly-generated hyper-rectangle. Once the splitting function ψ_i is determined, calculate its counterpart $1 - \psi_i$.

III (b). Compute the validity functions: determine the validity functions of two newly-generated validity regions by multiplication of all splitting functions from the root of the tree to the corresponding leaf.

III (c). Estimate the local model parameters: only parameters of the two LMs corresponding to the two newly-generated validity regions must be estimated using (4), and finally, the loss function for the current overall model must be computed. The other existing local models remain unchanged.

IV. Find the best division: the best LMs related to the lowest loss function value must be determined. The number of LMs is incremented: M → M + 1. If the termination criterion, e.g. a desired level of validation error or model complexity is met, then stop; otherwise, go to step II.

The maximum generalization and noteworthy modeling performance is among the salient features of the model identified by the HBT learning algorithm.

3. Dynamic vehicle identification

The dynamic model of a vehicle is schematically shown in figure 3. It includes three state variables, namely the longitudinal velocity (V_x), lateral velocity (V_y), and yaw rate (r) of the vehicle. Considering figure 3 and applying Newton laws, the mathematical relationship between the vehicle output variables can be derived. For instance, the longitudinal velocity can be expressed by:

$$\dot{v}_x = r v_y + \frac{1}{m}\{\left(F_{x,FL}+F_{x,FR}\right)\cos\left(\delta\right) - \left(F_{y,FL}+F_{y,FR}\right)\sin\left(\delta\right) + F_{x,RL}+F_{x,RR}-C_A v_x^2\} \qquad (14)$$

where, the subscripts *x* and *y* denote the longitudinal and lateral quantities, respectively; *F* is the force; the indices *FR*, *FL*, *RL*, and *RR* indicate the front left, front right, rear left, and rear right tires, respectively; and δ represents the steering angle.

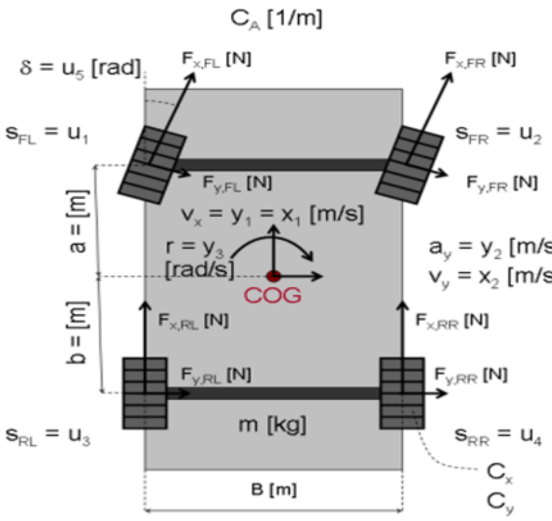

Figure 3. Schematic representation of vehicle dynamic model.

The mathematical equations for the lateral velocity and yaw rate can be similarly extracted. The parameters of the dynamic model in figure 3 include mass of vehicle (m), distance of front axle from vehicle's center of gravity (a), distance of rear axle from vehicle's center of gravity (b), air resistance coefficient (C_A), longitudinal tire stiffness (C_x), and lateral tire stiffness (C_y).

If the first four parameters are assumed constant, the longitudinal and lateral tire stiffness has to be estimated by means of a method. This hinders the analytic modeling of the vehicle dynamics and introduces more complexity into the modeling problem.

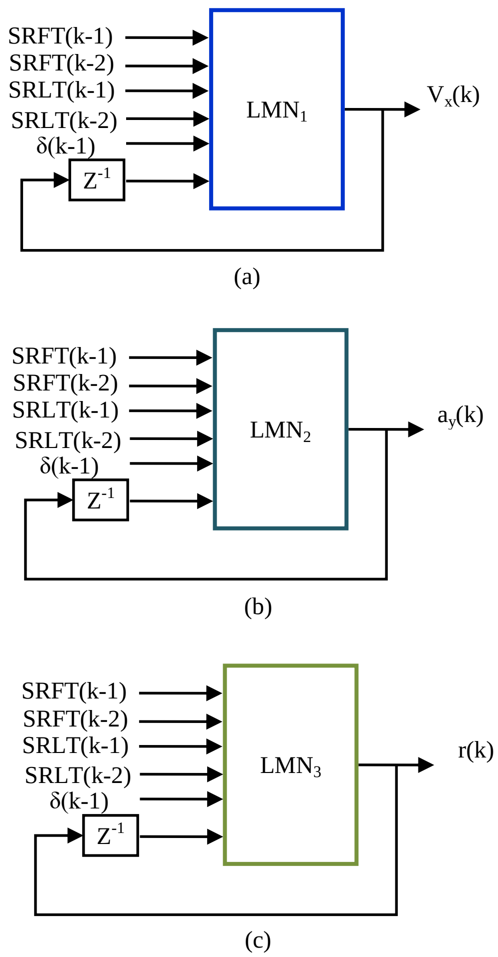

Figure 4. Structure of LMN for estimation of (a) longitudinal velocity, (b) lateral acceleration, and (c) yaw rate.

Hopefully, if a measurement-based identification is applied, there is no necessity for a direct estimation of tire's stiffness. The vehicle's longitudinal and lateral velocities as well as its yaw rate can be estimated using three individual LMNs, as shown in figure 4. Each LMN in in this figure is identified using the measurement data of the vehicle. For estimation of the longitudinal velocity of the vehicle, the previous values for the longitudinal velocity (V_x), SFRT, SFLT, and steering angle (δ) are used as the LMN's inputs. Similar input variables are considered for estimation of the lateral acceleration (a_y) and yaw rate (r) using LMNs, as shown in figure 4.

4. Identification results and discussion

4.1. Dataset and evaluation criteria

The proposed LMN will be used to identify the longitudinal velocity, lateral acceleration, and yaw rate of a Volvo V70 vehicle [10]. The experimental data has been collected for a Volvo V70 with the sampling interval T_s = 0.1 s. The dataset includes 2500 samples, as shown in figure 5. The first 70% of data samples are used to train LMNs and the remaining 30% serve as the test dataset to evaluate the performance of the identified models.

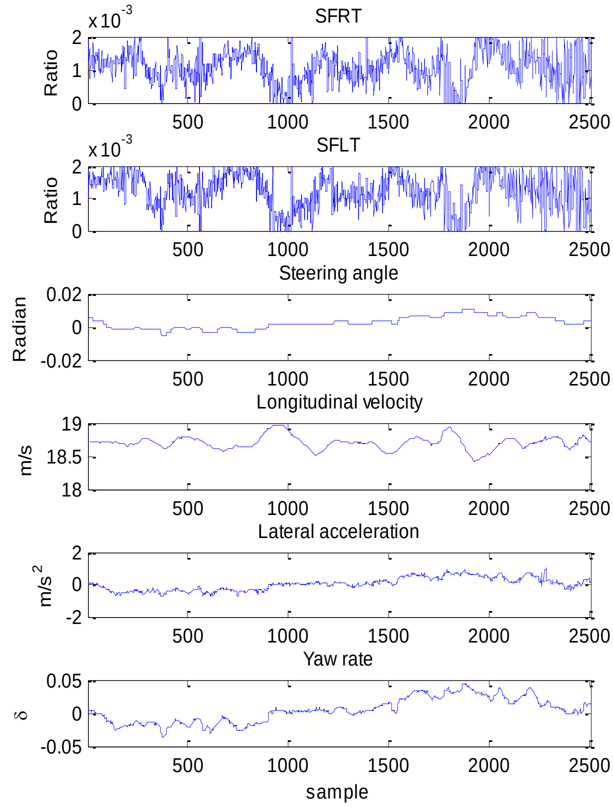

Figure 5. Inputs and outputs for vehicle identification.

In order to collect the real data, an rpm-meter has been used for measurement of the steering angle. Moreover, the slip of tires can be measured using the difference between the linear velocity of vehicle and the linear velocity of tire. The linear velocity of vehicle has been measured using a piezoelectric sensor. Also the linear velocity of the tire can be measured using the multiplication of angular velocity by radius of tire.

In order to investigate the identification performance, the root mean square error (RMSE) and the normalized mean square error (NMSE) are considered:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y(i)-\hat{y}(i)\right)^2} \tag{15}$$

$$\text{NMSE} = \frac{\sum_{i=1}^{N}\left(y(i)-\hat{y}(i)\right)^2}{\sum_{i=1}^{N}\left(y(i)-\bar{y}\right)^2} \tag{16}$$

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y\left(i\right) \tag{17}$$

where, y_i and $\hat{y}$ are the true and estimated values and N is the number of data samples. In addition, the performance of LMNs will be compared with the multi-layer perceptron (MLP) neural networks.

As stated earlier, in Section 3, three LMNs are constructed to estimate the longitudinal and lateral velocities as well as the yaw rate. The input and output for these LMNs are shown in table 1.

Table 1. Identification inputs and outputs.

Identification output	Identification inputs
Longitudinal velocity, $V_x\left(k\right)$	$V_x(k-1)$, SFRT(k - 1), SFRT(k - 2), SFLT(k −1), SFLT(k − 2), δ(k-1),
Lateral acceleration, $a_y\left(k\right)$	$a_y(k-1)$, SFRT(k - 1), SFRT(k - 2), SFLT(k −1), SFLT(k − 2), δ(k-1),
Yaw rate, $r\left(k\right)$	$r(k-1)$, SFRT(k - 1), SFRT(k - 2), SFLT(k −1), SFLT(k − 2), δ(k-1),

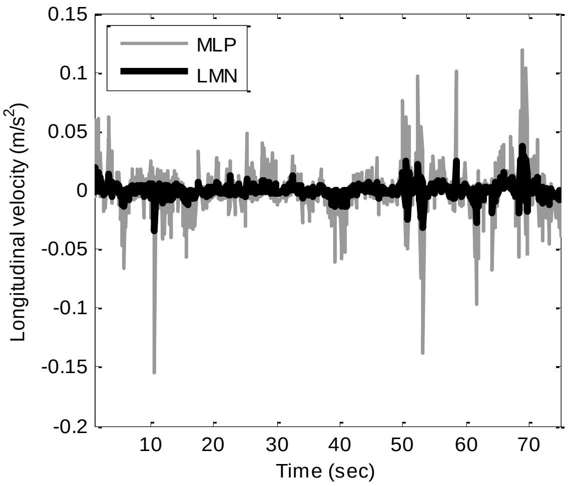

Figure 7. Estimated longitudinal velocity error.

Table 2. Results of longitudinal velocity identification.

	LMN	MLP
RMSE	0.0059	0.0203
NMSE	0.0024	0.0283

4.2. Identification of longitudinal velocity

An LMN with five neurons provided the best performance for the longitudinal velocity estimation. The actual and estimated longitudinal velocities for the test data are shown in figure 6. Moreover, a comparison between the estimation errors of the LMN and MLP neural networks is presented in figure 7, stressing on the superior performance of LMN. The numerical evaluation of both the LMN and MLP neural networks is also presented in table 2. According to this table, the reduction in value for the estimation error based on the RMSE index using LMN with regard to MLP is about 72%, and based on the NMSE index is 91%.

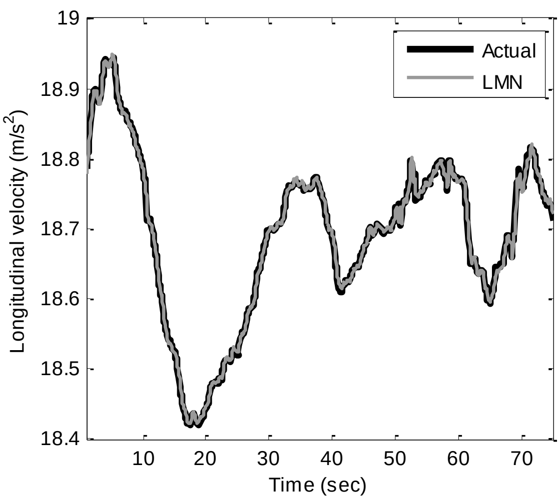

Figure 6. Estimated longitudinal velocity.

4.3. Identification of lateral acceleration

The result of lateral acceleration identification is shown in figure 8. It can easily be seen that there is a close match between the actual and estimated accelerations. A graphical comparison between the estimation error of the LMN and MLP neural networks is depicted in figure 9. The numerical evaluations between the LMN and MLP neural networks, presented in table 3, demonstrate a favorable performance of the proposed identification method. As shown in this table, the reduction in estimation error based on RMSE using LMN in comparison with MLP is 71%, and according to NMSE it is about 91%.

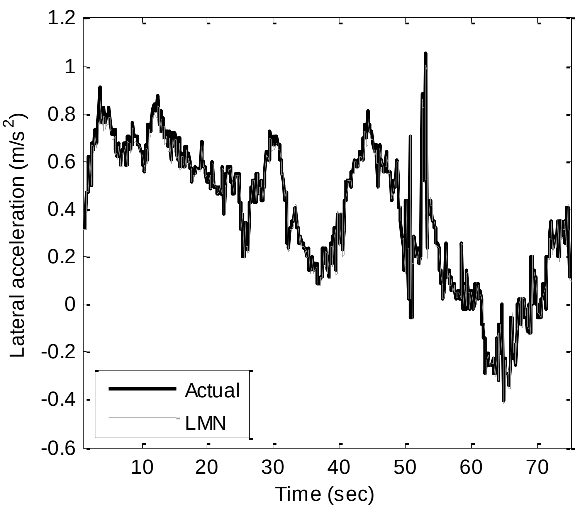

Figure 8. Lateral acceleration estimation.

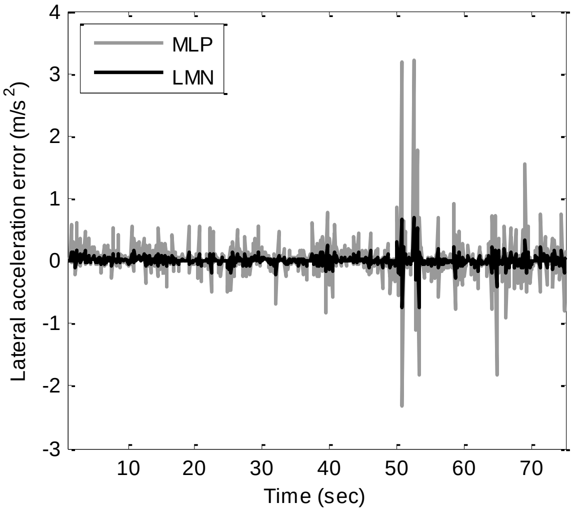

Figure 9. Lateral acceleration estimation error.

Table 3. Results of lateral acceleration identification.

	LMN	MLP
RMSE	0.0846	0.2921
NMSE	0.0827	0.9851

4.4. Identification of Yaw Rate

The final identification case focuses on estimation of the vehicle's yaw rate. An LMN with four neurons resulted in the lowest validation error. Figure 10 shows the LMN estimation of the yaw rate against the actual measurements. Similar to the previous case studies, a graphical comparison of the estimation error of the LMN and MLP neural networks is illustrated in figure 11, and the numerical evaluations presented in table 4 confirm a more satisfactory performance of the proposed approach.

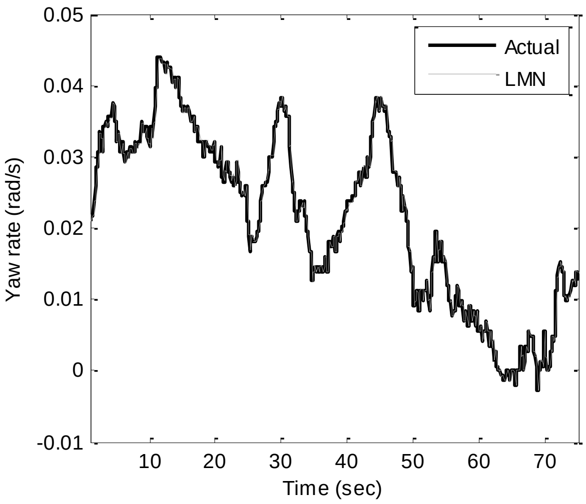

Figure 10. Yaw rate estimation.

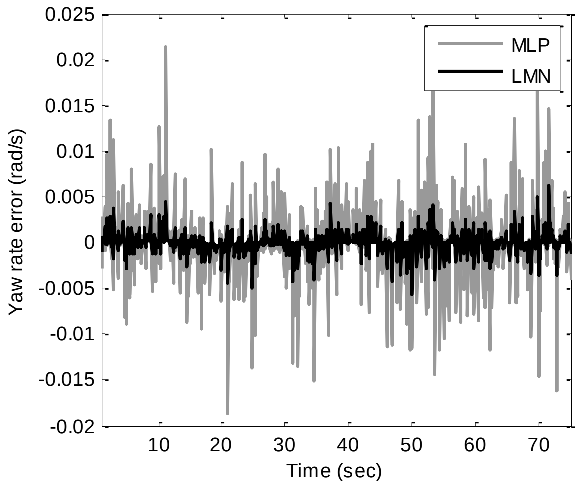

Figure 11. Yaw rate estimation error.

Table 4. Results of yaw rate identification.

	LMN	MLP
RMSE	0.0012	0.0041
NMSE	0.0090	0.1097

The identification process of the yaw rate depicts a reduction of 70% in the estimation error on the basis of RMSE and a reduction of 92% based on NMSE using LMN relative to MLP, as shown in table 4.

In the control purpose of vehicle, an accurate identification of the longitudinal velocity, lateral acceleration, and yaw rate is very important. The exact estimation of these variables leads to the appropriate behavior in the yaw controller system. As a result of the identification process, the vehicle dynamics can be stabilized using this controller via the actuator system, e.g. distributed breaking system.

According to the results of the system identification based on LMN and MLP, the LMN approach decreases the run-time of processing for about 16% in comparison with MLP. Also the estimation error is reduced in the identification process using LMN relative to MLP. As a result, LMN can estimate these variables more accurately and more rapidly than the simplest method, e.g. MLP. Moreover, the identification of these variables using LMN has been carried out as well as with a fewer number of datasets.

5. Conclusion

In this paper, I proposed a data-driven identification strategy for the dynamic modeling of vehicles. In the proposed method, a local model network was employed for the dynamic estimation of the longitudinal velocity, lateral acceleration, and yaw rate of the vehicle. The proposed LMN was composed of local linear models and their associated validity functions, each describing a specific operating regime of the vehicle dynamics. LMN was trained using the heuristic and fast HBT learning algorithm, and then applied for estimation of the longitudinal velocity, lateral acceleration, and yaw rate for a Volvo V70 vehicle. The identification results and comparison with an MLP neural network demonstrated the promising performance of the proposed approach. Consequently, the identification of variables using LMN relative to MLP depicts a reduction of about 70% in the estimation error based on RMSE and a reduction of 90% based on NMSE. Also the rapid convergence of the estimation process is more revealed in LMN due to the reduction in run-time.

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نشریه هوش مصنوعی و داده کاوی

شناسایی هوشمند دینامیک خودرو براساس شبکه مدل محلی

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چکیده:

در این مقاله، یک نگرش هوشمند برای شناسایی دینامیکی متغیرهای خودرو ارائه شده است. نگرش توسعه داده شده، شبکه مدل محلی با کارآیی بالا براساس شناسایی داده‌های استخراج شده از سیستم خودرو می‌باشد که برای تخمین متغیرهای سرعت طولی، شتاب جانبی و سرعت زاویه‌ای حول محور عمودی مورد استفاده قرار می‌گیرد. شبکه مدل محلی ارائه شده به مدل استاندارد خودرو به عنوان پیش‌فرض نیازی نداشته و تنها از داده‌های اندازه‌گیری شده برای شناسایی دینامیک خودرو استفاده می‌نماید. شبکه مدل محلی بوسیله الگوریتم درختی دودویی مرتبه‌ای آموزش داده می‌شود که بدین وسیله به یک شبکه با حداکثر قابلیت تعمیم‌پذیری با بهترین ساختار خطی یا غیرخطی تبدیل می‌شود. روش ارائه شده، بر روی داده‌های اندازه-گیری شده از خودرو ولوو بکار گرفته شد که به منظور تخمین سرعت طولی، شتاب جانبی و سرعت زاویه‌ای عمودی آن استفاده می‌شود. نتایج حاصل از شناسایی دینامیک سیستم نشان می‌دهد که شبکه مدل محلی قادر است بدقت متغیرهای دینامیکی خودرو را شناسایی نماید. بعلاوه، مقایسه نتایج حاصل از شبکه مدل محلی با شبکه عصبی پرسترون چند لایه حاکی از عملکرد بهتر نگرش شناسایی ارائه شده است.

کلمات کلیدی: شبکه مدل محلی، درخت دودویی مرتبه ای، دینامیک خودرو، شناسایی، شبکه عصبی.