Accuracy of Friction Estimation during Driving

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Abstract

Accuracy of online friction estimation depends on the ability of the sensors to capture information about the current interaction between road and tire. Sensors have different characteristics and limitations, so depending on the situation their contribution varies.

In this work we investigated the construction of a model that maps a driving situation (represented as sensor data time series) to the accuracy of friction estimation that can be expected for this particular situation. To train such a model from data, we used „Echo State Networks", a method for constructing and training large Recurrent Neural Networks.

Kurzfassung

Die Genauigkeit, mit der die Bodenhaftung eines Fahrzeugs auf einer Fahrbahn während der Fahrt abgeschätzt werden kann, hängt von den Fähigkeiten der verwendeten Sensorik ab. Sensoren haben unterschiedliche Charakteristiken und Beschränkungen, die je nach Fahrsituation ihre Aussagekraft und damit auch die Genauigkeit des Bodenhaftungsschätzung beeinflussen.

In dieser Arbeit untersuchen wir die Möglichkeit, von der aktuellen Fahrsituation nicht nur die aktuelle Bodenhaftung zu schätzen, sondern auch die Genauigkeit dieser Schätzung. Um aus den Sensor-Daten die aktuelle Fahrsituation wird ein Verfahren zur Zeitreihen-Analyse verwendet, nämlich „Echo State Networks", ein Verfahren zur Konstruktion und Training von großen Rekurrenten Neuronalen Netzwerken.

1. Introduction

Knowing the actual friction between road and tire is essential for avoiding accidents, in particular, when road conditions change during driving. Low friction conditions should lead to a warning signaled to the driver, and safety measures, e.g., carried out by the Automated Emergency Braking System (AEB).

In [5], we describe experiments with cars equipped with both on-board and additional advanced sensors. We showed that the friction coefficients for the road, and individually for each wheel can be estimated from sensor data using „Echo State Networks"

(ESNs) [4] [6], a method for constructing and training large Recurrent Neural Networks (RNNs). This method was chosen because the dynamics of driving situations can only be identified by analyzing the time series of sensor data. RNNs, and in particular ESNs, are very powerful in performing such time series analysis.

However, it turned out that the accuracy of friction estimation varies during driving. Estimation accuracy was bad, for instance, when the vehicle is not exposed to any acceleration in any direction. On the contrary, estimation worked very well during acceleration and cornering, in particular, during sinus driving.

In this paper, we describe how friction estimation can be enhanced by additionally estimating the accuracy. Accuracy of friction estimation depends on the current interaction between road and tire, and the ability of the sensors to capture information about it. Sensors have different characteristics and limitations, so depending on the situation their contribution varies.

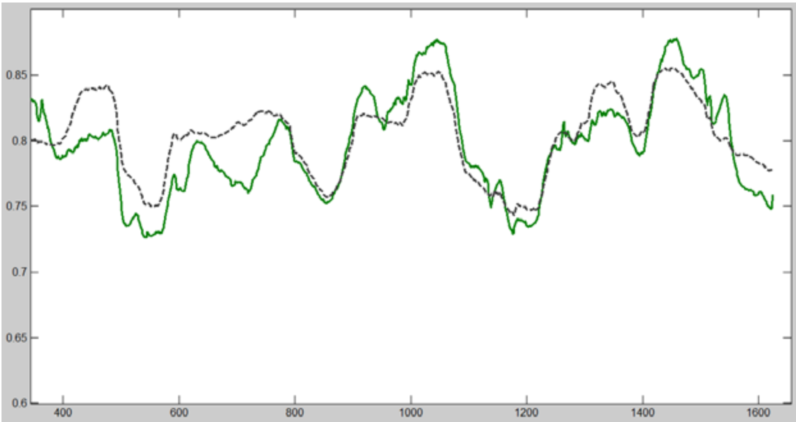

Figure 1: The accuracy of estimating the friction potential of a wheel is varying during a drive of approximately one minute.

Again, Echo State Networks are used to determine accuracy of friction estimation. We built an ESN model that estimates the accuracy of friction estimation varying over time during driving.

We start with the discussion of some related work (in section 2). Then the measurements and the sensor data used are described (section 3). The technical approach we used to estimate accuracy is detailed in section 4. Section 5 shows how 95% confidence intervals can be obtained to be utilized by an Automated Emergency Braking System (AEB). Applying our approach on tire friction estimation has lead to results which are presented in section 6.

2. Related Work

There are numerous approaches on online failure estimation and prediction, see [9] for a comprehensive survey. The choice of a method is influenced by the task to be solved (e.g. should the failure (or accuracy) be quantified, or is it sufficient just to show the existence of a failure), and by the data available (e.g. is it possible to determine failure/accuracy from the current state of the system, or is it necessary to analyze the time series of system states).

Applying the taxonomy of [9] on friction estimation leads to time series analysis methods, like autoregressive Methods (like ARIMA) [2], Hidden Markov Models [1], and Recurrent Neural Networks (RNNs) [3]. Echo State Networks (ESNs) is an approach of constructing and training RNNs in a way that enables fast and stable training of large RNNs (having several thousand internal nodes). The learning power of large ESNs offers the capability to detect complex dynamical patterns in long multivariate time series.

There are also methods which can be used to investigate how confident a trained model is in the accuracy of its own result. For instance, one could run a model with different levels of noise added to the same input data. If the model's result remains stable for reasonable amounts of input noise, it can be inferred that the model is rather 'confident' in its result. Extending such investigations to processes in time leads to Monte Carlo simulation [7]. In the domain of regression methods, Gaussian Process Regression [8] offers a methodology to compute the distribution of a result depending on its correlation with the data used for training.

Note that in most cases these methods are used with the assumption that the 'measurement noise' is Gaussian with constant variance for all data points. As measurement noise is a synonym for measurement accuracy, or measurement error, it is obvious that this assumption does not hold for friction estimation, because of sensor characteristics in responding differently in different driving situations.

3. Data Acquisition

Sensor Data

Measurements were conducted on Contidrom proving ground with an Audi A4 Avant 1.8 TFSI including several driving maneuvers. Three different tire types with different inflation pressures were evaluated on dry and wet road surfaces.

The wind velocities on the proving ground were $\leq$ 5.2 m/s during all measurements and the road surface temperature varied between 16.5 and 30 °C. Quasi-steady-state driving maneuvers of at least 15 minutes were conducted before starting the measurements to ensure that the tires were at operating temperature. The inflation pressures were set at operating temperature of the tires. Altogether, 98 driving maneuvers have been performed.

Both the standard on-board sensors of the vehicle as well as an advanced measurement equipment to evaluate the vehicle dynamics have been used.

The on-board vehicle sensors record the wheel speeds of all four wheels, the steering wheel angle, the vehicle's longitudinal velocity in the COG (centre of gravity), the engine's rotational speed, the engine torque, the accelerator pedal position, the vehicle's yaw rate, and the environment temperature.

Figure 2: The test vehicle with additional advanced sensory equipment

Advanced vehicle dynamics measurement equipment included optical speed sensors, fibbers-optic gyro for rotational speeds, and braking pressure measurements.

Determination of the true Friction Potentials (Reference Values)

The true friction potentials, which should be the output of the learned friction model, are determined based on additional information about the tire, the road surface, and the car

For each combination of road surface and mounted tire, a global friction potential μ_G has been identified based on driving manoeuvres near the limits of the maximum achievable accelerations. To ensure that the driving manoeuvres were at the limits, the slip angles at the maximum lateral acceleration $a_{M,y}$ were compared to lateral tire characteristics measured on a test bench. Based on a simplified vehicle model, the following relationship between the friction potential $\mu_{G,y}$ in lateral direction and $a_{M,y}$ is assumed:

$$\mu_{G,y} = \frac{a_{M,y}}{g}. \qquad (1)$$

Longitudinal tire characteristics were not available, so the identified friction potential is only based on the measured accelerations achieved during braking. Usually, the longitudinal potential of tires is higher, but the comparison between the achieved longitudinal and the lateral accelerations showed similar results. So it was further on assumed that the friction potential was the same in longitudinal and lateral direction:

$$\mu_{G,x} \approx \mu_{G,y} \approx \mu_G. \qquad (2)$$

In addition to the global friction potential μ_G, also wheel-individual friction potentials $\mu_{R,i}$ are estimated, see equation (3). They indicate the maximum transmittable forces on each tire and can be used to enhance the AEB strategy.

$$\mu_{R,i} = \mu_G \cdot \mu_{meas}(F_{z,i}(t)). \qquad (3)$$

The value μ_{meas} is a function of the time variant dynamical vertical force $F_{z,i}$ acting on each tire i and is determined based on the lateral tire characteristics measured on a tire test bench. The dynamical vertical forces $F_{z,i}$ were calculated using a two-track vehicle model validated using measurements.

4. Accuracy Estimation

In addition to a model for friction estimation (whose construction we have described in [5]), we want to build a second model which estimates the accuracy, i.e. *the mean absolute error*, of the first model for a particular driving situation.

A model for estimation the accuracy of friction estimation is obtained in a 2-step procedure.

In the first step, we determine how accurate the friction can be estimated for the training data obtained from driving maneuvers on the training course (section 3).

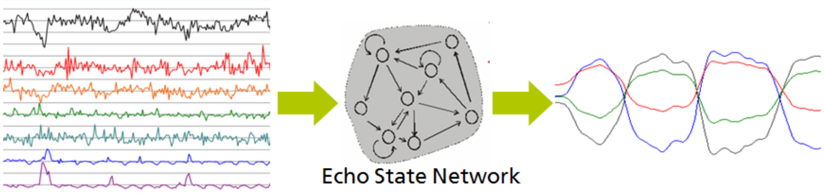

Figure 3: ESN models are trained that map sensor data time series to friction values

Of course, accuracy of a model can only be determined on data *not* used for training the model. In order to utilize the limited available driving data in an optimal way, we applied Leave-one-out Cross Validation (LOOCV).

During LOOCV, the following process is repeated for each driving maneuver: one driving maneuver is selecting for test; then a friction estimation model is trained using data of all other maneuvers. This model is used to estimate the friction on the maneuver not used for training. The difference between the estimated friction and the true one (reference values, see section 3) constitutes the estimation error, i.e. the accuracy. By repeating this procedure, we get the accuracy (i.e. absolute error) for all data points of all maneuvers.

In the second step, we train a model to estimate the accuracy of friction estimation. The input of the model is again the sensor data like in the first step. The output is not the friction (like in the first step) but the *absolute error* of the friction estimation determined in the first step.

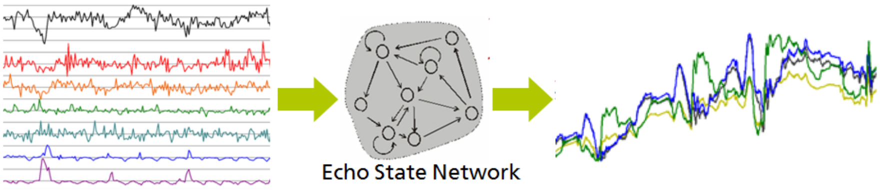

Figure 4: ESN models are trained that map sensor data time series to absolute error in friction estimation.

Again we apply LOOCV in order to use as much as possible of the available data for training the models. This way we estimate the absolute error on the estimation for all maneuvers.

The output of the model for a particular driving situation x_t ant time t is the *mean* absolute error of the friction estimation for x_t.

5. Estimation of Worst Case Accuracy for AEB

An Automated Emergency Braking System (AEB) has to avoid two kinds of situations. First, it should avoid that the car collides with an obstacle or reduce the impact energy to reduce injury severity. Secondly, it has to avoid that automatic braking starts too early or when there is no emergency situation. Investigations show that alarms that are perceived as unhelpful lead to decreased trust in the system und would not be accepted by the drivers. Both situations can occur either if friction is underestimated (=>warning and intervention earlier than necessary) or overestimated (=> collision).

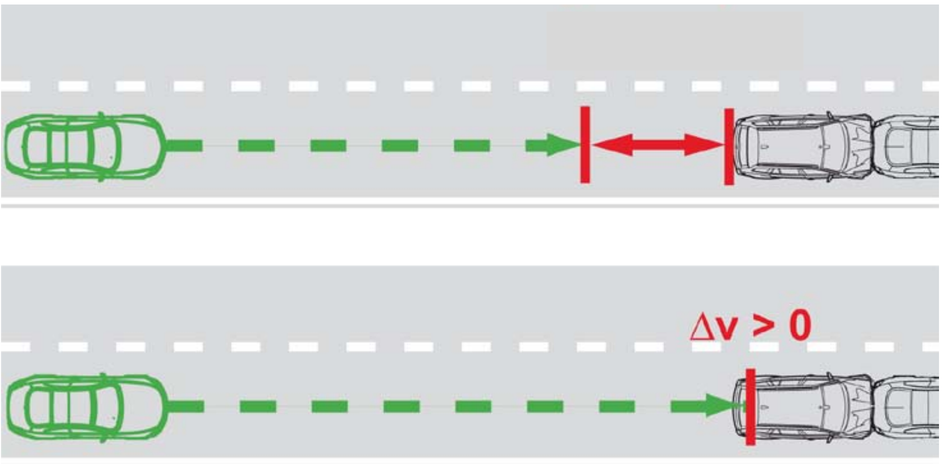

Figure 5: Automated braking situations when friction is underestimated (above) and overestimated (below).

Instead of getting friction estimation and its mean absolute error, the AEB needs worst case friction estimation. In case of a possible collision, the AEB could first trigger some slight deceleration of the car while continuously analyzing further friction estimations. It can be assumed that deceleration situations lead to more accurate friction estimations. If the danger of collision still persists even after deceleration, the AEB has to trigger automatic braking.

The accuracy estimation described in section 4 computes the mean absolute error without any standard deviation or probability distributions. This has to be modified to obtain a worst case estimation.

For this reason, we shift and scale the error estimation to obtain a worst case estimation wce such that in 95% of all cases it exceeds the real estimation error. I.e. we determine offset a and scaling factor b such that for 95% of all data points x, condition (4) holds.

$$wce(x) = a + b * estimatedError(x) > realError(x) \quad (4)$$

Condition (4) can be satisfied for many combinations of a and b. In order to minimize false alarm rate, a and b can be chosen to minimize the sum of $wce(x)$ on all data points x.

6. Results

We applied the procedure described in section 4 on the data of the experiments described in section 3. In a 2-step procedure we obtained for each data point x

a) the 'real' error, i.e. how accurate the friction at this data point can be estimated using an ESN model (step 1).
b) an estimate of the mean absolute error at x obtained from a second ESN model (step 2).

It showed that a model for estimating the absolute error can be learned. This is not a trivial result, as learning of an error model is harder than learning the friction model. We also tried to learn an error model using another approach (ESN in combination with Gaussian Process Regression) not described in this paper. This approach totally failed, i.e. the estimated errors showed very low correlation with the real errors.

We then shifted and scaled the mean error estimation obtained from the ESN model according to section 5 to obtain a worst-case friction estimation which can be used by an AEB. Figure 6 gives an impression about how error varies over time (dotted line), and how worst case error estimation can provide an upper bound for the error to be valid in 95% of all data points.

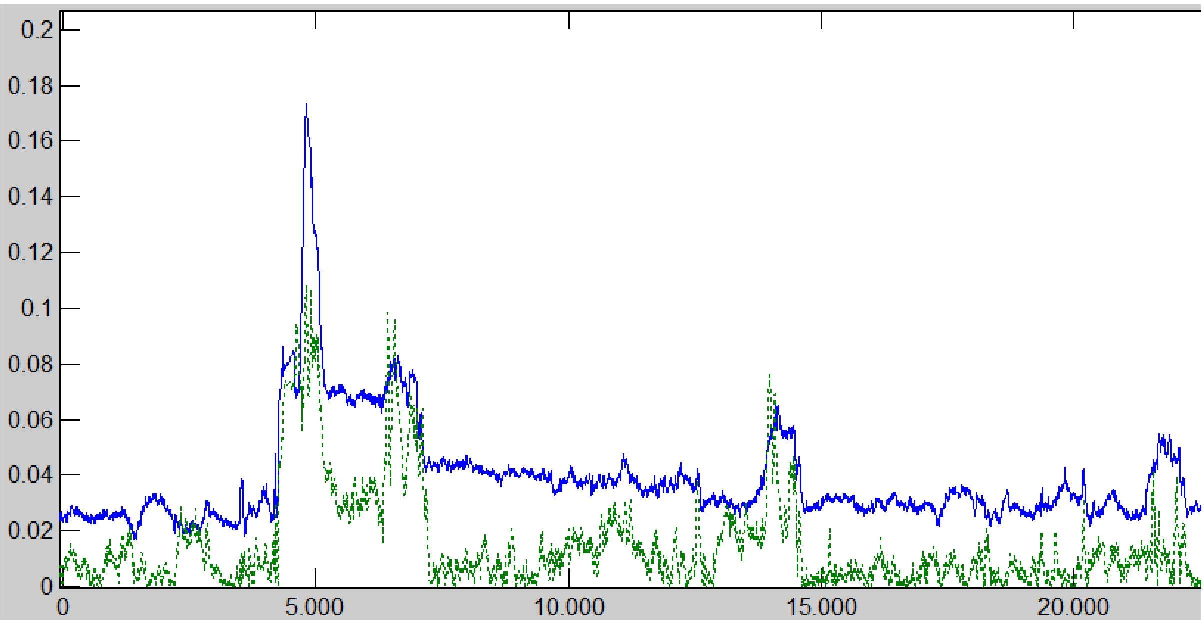

Figure 6: Friction error (dotted line) and worst case error estimation (solid line)

7. Conclusions

Previously we have shown that tire friction can be estimated from sensor data using Echo State Networks (ESNs) [5]. But it has turned out that the error of friction estimation varies too much to be used directly for AEB.

So we investigated the hypothesis whether the error in friction estimation can be estimated by ESN models as well. We developed a 2-step procedure to compute and validate ESN models for error estimation. In an additional step we transformed the model output to obtain a worst case error estimation of 95% confidence to be usable for an AEB.

This paper shows a principle approach to solve the problem of error estimation. This approach can, of course, be further refined and improved. In particular, the requirements of AEBs have to be explored more in detail and more specialized error estimation can be designed according to the particular behavior of the AEB to treat certain situations.

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