Pilot Study: Road–Tyre Friction Prediction by Statistical Methods and Data Fusion

Lauri Lovén*, Ekaterina Gilman*, Jukka Riekki*, Esa Läärä†, Timo Sukuvaara‡, Kari Mäenpää‡, with Mikko J. Sillanpää† and Susanna Pirttikangas*

* Center for Ubiquitous Computing
University of Oulu
Oulu, Finland,
{first.last}@oulu.fi

† Applied Mathematics and Statistics
University of Oulu
Oulu, Finland,
{first.last}@oulu.fi

‡ Arctic Research Center
Finnish Meteorological Institute
Sodankylä, Finland,
{first.last}@fmi.fi

***Abstract*—In this article, we report a pilot study to predict tyre–road friction by data fusion and statistical inference methods. We trained a prediction model, based on linear regression, with weather data, traffic data and official road database information as covariates, and friction measurements of four separate test runs as ground truth. We assessed the validity of the model by standard diagnostics as well as cross validation. The results indicated that the method is promising; however, more data are required to ensure the model is not overfitted.**

I. Introduction

Weather prediction is of great interest for many domains. Transportation, in particular, values weather prediction as it improves driving safety and sustainability and, in general, helps to reduce costs [1], [2].

Predicting the tire–road friction coefficient is of particular interest, as slippery roads are demanding for both the road maintenance authorities as well as the drivers. Friction depends on diverse factors like weather, road material and traffic density, varying from one location to another. However, it is very challenging to provide reliable online predictions of friction by ordinary measurement approaches. New methods thus need to be developed to predict friction in different locations from the data available either from environmental sensors or from drivers.

As this research contains theoretical uncertainties (due to small data set sizes), we perform an exploratory study with the intent of building a simple prediction model and measuring its quality.

II. Data

This study was based on data fusion. Geospatial data, weather data, traffic fluency data, and actual friction measurements data were fused together in an effort to build a reliable prediction model.

Friction sensor data: The Teconer RCM411 friction sensor data comprised four measurement runs of almost identical routes (Figure 1), starting at the Linnanmaa campus area near 65.05° N and 25.45° E, and visiting the southern part of Oulu urban area. The data included friction values and GPS locations, taken once per second during each measurement run.

Weather Station Data: A Vaisala DSC111 weather station, located nearby (see Figure 1), provided multiple weather related measurements as well as local friction measurements at the weather station location every 15 minutes. As the measurements were so sparse, we interpolated the values (by a monotonic spline [3]) to accommodate for the once-per-second sample rate of the Teconer device.

Figure 1: City of Oulu, Finland. Vaisala weather station location marked with a cross and a red dot; Noptel traffic sensor with a cross and a yellow dot; Teconer friction measurements as blue dots.

Traffic Sensor Data: For information on traffic flow, we aggregated indications of passing cars within a sliding two-hour time window, as produced by a Noptel laser sensor array. All 5 lanes of the observed location on Merikoskenkatu, a central hub in Oulu city, were included.

Geospatial information was retrieved from the Digiroad[1], a national database containing the geometry of the Finnish road and street network as well as a number of *features* related to the road type and the traffic on it.

We used the Digiroad spatial data for two purposes: to map-match the Teconer device GPS locations to nearest road segments; and to fetch the features of each road segment map-

[1]Finnish Transport Agency, "Digiroad – the Finnish road network in digital format", URL http://www.digiroad.fi/dokumentit/en_GB/documents/.

Table I: Data size breakdown.

	Run 1	Run 2	Run 3	Run 4	**Total**
Observations	2188	1940	2084	1660	**7872**

matched. The road segment features used in this study included the presence of traffic lights (TL) and predestrian crossings (PC), the type (VT) and service level (FT) of the road segment as well as the average speed limit along the segment (AS).

III. Methods

Our aim was to predict FTe on a given road segment (with road segmentation defined in the Digiroad database using the other variables as covariates.

To find the road segments for each FTe value, we had to map-match the GPS coordinates of the FTe measurements. The friction measurements from both the Teconer and the Vaisala devices (Fte, FVa) ranged in]0, 1[. To avoid predictions outside the range, the values required a transformation to]-∞, ∞[. We chose the *logit* transformation[2] [4]. The variables FTe and FVa thus transformed were appended either with the $_l$ subscript or *_l* postfix, as applicable.

Following Juga et al. [5], we further applied a log transformation on the thicknesses of the water, ice and snow layers ($_{log}$ subscript or *_log* postfix). Further, we applied the following (slightly modified version of) Juga et al.'s negative logarithm based conversion to all three temperatures (TRo, TAi, TDe):

$$\text{neglog}(x) = -\log\left(\max(\text{x}) + 0.1 - \text{x}\right)$$

The variables with the neglog transformation were appended either with the $_n$ subscript or *_n* postfix, as applicable.

Finally, we also investigated the difference between road temperature and dew point temperature, TDi = TRo − TDe, as suggested by Juga et al. – or, in fact, its more stable neglog transformation.

The final model we settled on, after compensating for collinearity and measuring model fit criteria, has the following form:

$$\begin{aligned}\text{FTe}_l = {} & \alpha_0 + \alpha_{\text{TLi}} + \alpha_{\text{VTy}} + \alpha_{\text{FTy}} + \alpha_{\text{ASp}} \\ & + \beta_{\text{TFl}} \times \text{TFl} + \beta_{\text{TRo}_n} \times \text{TRo}_n + \beta_{\text{TDi}_n} \times \text{TDi}_n \\ & + \beta_{\text{RIn}} \times \text{RIn} + \beta_{\text{CPr}} \times \text{CPr} + \beta_{\text{Wa}_{\text{log}}} \times \text{Wa}_{\text{log}} \\ & + \beta_{\text{Ic}_{\text{log}}} \times \text{Ic}_{\text{log}} + \beta_{\text{Vi}} \times \text{Vi} + \varepsilon\end{aligned}$$

Here, α_0 denotes the overall intercept, the other α's the category level adjustments, and the β's the slope coefficients of the quantitative variables, to be estimated by linear regression. ε stands for Gaussian noise.

IV. Results

Using one run as a test data and others as training data, the predictions for run 2 and 4 are not quite as well on the mark as those for 1 and 3 (Figure 2). This is the direct result of sparseness of data: runs 2 and 4 were very much on the edge of the covariate value space, forcing extrapolation when left out of the training data.

[2]As the transformed measurements were never 0 or 1 in the data, no manipulations were required to avoid singularities.

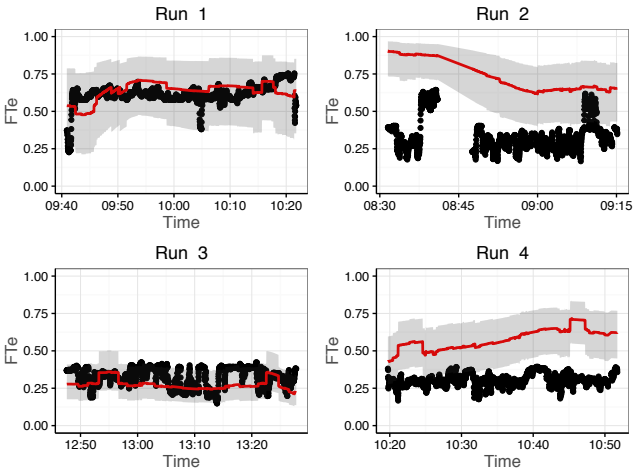

Figure 2: Friction predictions for all four runs with by-run cross-validation. Black dots mark the ground truth, while red line is the prediction. The gray area marks the 95% confidence band.

V. Conclusion

We have built a statistical prediction model for tyre–road friction, based on simple linear regression and data fusion. The predictions by the model appear reliable within the scope of available data; however, due to small amount of data available for the study, the model likely requires augmentation for use in a real-world scenario.

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[3]Data to Intelligence project, URL http://www.datatointelligence.fi/.