Analysis of the relationship between SCRIM and Texture Depths

Tim Hok Him Lai

Rachel Cardell-Oliver[1], Yuxia Hu[2]
1. Computer Science and Software Engineering
2. Civil, Environmental and Mining Engineering
The University of Western Australia

Simon Beard
Main Roads Western Australia

Abstract

Main Roads Western Australia (Main Roads) uses various methods to monitor and evaluate road skid resistance and surface texture in Western Australia. SCRIM is a road survey vehicle to measure wet skid resistance (combined microtexture and macrotexture), and Texture Depth is a measure of macrotexture. Current data collection through Sideways Coefficient Routine Investigation Machine (SCRIM) is costly. Another concern during SCRIM testing is the water consumption and refilling procedure. Main Roads wishes to understand whether texture and other variables can be used to accurately predict SCRIM values, which would reduce the need for data collection.

The statistical analysis shows that the correlation between SCRIM data and Texture is minimal or nearly nonexistent. However, the predictive modelling process showed that texture could be combined with other features for SCRIM coefficient prediction. The feature importance process shows that Region Information, Annual Rainfall, Speed Limit, Traffic Volume, Lane, and Texture are the most important factors affecting SCRIM model development. All this information could assist Main Roads in targeting and locating potential zones that would refine the risk management and data collection process.

1. Introduction

Road crashes are usually caused by a combination of factors, including the driver, the vehicle, and the road conditions. Despite the multiple factors, there is evidence in the literature that crashes are related to pavement characteristics, such as skid resistance and texture. In New Zealand, Davies et al. (2005) showed that different natural factors contribute to crashes. Examples include road geometry (horizontal curvature, gradient, and crossfall), road surface conditions (roughness, rut depth, texture depth, and skid resistance), and carriageway characteristics (region, urban/rural environment, and traffic flow).

Road agencies regularly monitor pavement parameters such as skid resistance and texture depth. Although the correlation has been proven consistently, it is difficult to quantify precisely (Pérez-Acebo et al., 2020). Few papers have investigated their correlation since one measures microtexture and the other measures macrotexture. There are also differences in the approaches and methodologies for managing roads due to the differences in climate and typical road geometry across countries and regions. Therefore, not all road agencies' policies and methods can be implemented directly in Western Australia.

Current data collection through Sideways Coefficient Routine Investigation Machine (SCRIM) is costly. Furthermore, previous research found no significant correlation between skid resistance, texture depth, and road crashes in Western Australia (Cairney and Bennett, 2013). The pavement management policies and guidelines established by other countries and regions may not be suitable to Western Australia due to the variations in geographical locations, climate, and road surface conditions. Based on the above, conducting local scale research (within the state or at the regional level) is necessary.

This project is to investigate the relationship between SCRIM and Texture Depths for a range of road types and environments in Western Australia. The data collected by Main Roads from different surveys serve different purposes. All data sets need to be reconciled before they can be used in data analysis. Pavement characteristics, road geometry, climate, region information, and traffic volume data will be used in the analysis to identify the correlation between SCRIM and texture depth by applying data science techniques. Statistical analysis and predictive model will be used in this study to determine whether SCRIM data are predictable. The feature importance process will be performed to identify the most relevant factors affecting the SCRIM model development. All this information would allow recommendations regarding the data collection plans to ensure that the samples Main Roads were obtaining were representative.

2. Process

2.1 Data Collection

To quantify the relationship between SCRIM and Texture depth in Western Australia, both variables had to be collected a wide-range scale. Many of these data were already collected and maintained at Main Roads, which provided the data in use in this research. This project involves merging and analysing multiple datasets from different resources. Generally, the data can be categorised into five categories: Pavement characteristics, Road Geometry, Climate, Region Information, and Traffic Volume. In addition, data acquisition is required to convert the data into a dedicated dataset for this project's analysis and research purposes.

Main Roads periodically collected skid resistance and texture depth data. The skid resistance data were collected periodically (approximately 5-year intervals) through SCRIM testing on a sample of spray seal, asphalt, and micro surfacing surfaces. Previously, Main Roads conducted targeted SCRIM testing in December 2012 and between May and June 2018. The texture depth data has been collected using a network-wide texture survey on the sealed road network. The survey was conducted to determine the mean profile depth (MPD) of the surface. Currently, these surveys are conducted on a two-year cycle (1/2 network each year.

Geometry data and climate data are also important in this study. Geometry data for roads was obtained from Main Roads in another dataset. These data included information about road geometry (e.g., cross fall, grade, curves radius, etc.). Information about regions and traffic volumes are also included in other datasets provided by Main Roads. Four regions are recorded in the dataset: Greater Southern Region, South West Region, Goldfields Esperance Region, and Metropolitan Region. Climate data were collected from the Bureau of Meteorology (BOM) and the Australian Building Codes Board (ABCB).

2.2 Data Processing

This project requires merging multiple datasets from different sources. Processing steps are collecting data, merging, cleaning, and organising into a single dataset for the tasks to follow. The datasets given by Main Roads use the Integrated Road Information System Road (IRIS) and Straight Line Kilometres (SLK) for network referencing. Since each dataset is measured differently and serves different purposes, their recorded intervals are usually different. For example, SCRIM data is recorded every 5 meters, whereas texture data is recorded every 100 meters. As a result, it is necessary to create a dynamically segmented dataset with accurate records. In order to integrate data, it was suggested to use the parameters from the IRIS network referencing system. Road Numbers, Carriageways, and Straight Line Kilometers (SLK) are used in this case.

The Texture dataset is joined with other datasets based on Road Number, Carriageway, and SLK parameters. Road geometry, traffic volume and climate data were integrated into the dataset. As SCRIM data are measured at 5-meter intervals, special treatment is necessary for them to match the newly created dataset recorded at 100-meter intervals. For each interval, the minimum, average, median, lower percentile (25^{th}) and upper percentile (75^{th}) of SCRIM variables in that interval were used as the predictor variables for experiment and analysis. Compared to the 2018 SCRIM dataset, the 2013 SCRIM had already been merged and edited by Main Roads staff. For comprehensiveness and accuracy, this study used and collected data from 2013 instead of the most recent one (2018).

2.3 Analysis Method and Modelling

Statistical analysis was conducted using the Linear Regression Model to determine the correlation between SCRIM and Texture. Main Roads recommended using the Lower Percentile (25^{th}) of SCRIM as the predictor variable since it is an empirical variable commonly used in the field. The Pearson correlation coefficient (R) and Coefficient of determination (R^2) is used to determine the correlation between two variables. The Pearson correlation coefficient (R) is used to compute the correlation between SCRIM and Texture. The Coefficient of determination (R^2) is used to calculate how much variance can be explained by the predictor variable.

Following that, the study experimented with various predictive models to determine whether texture and other variables can be used to predict SCRIM values accurately. The model used the predictor variable of the Lower Percentile (25^{th}) of SCRIM. The model was trained with other features (such as Pavement Characteristics, Traffic Volume, Climate, Region Information and Road Geometry). Testing and experimenting with several traditional machine learning models were conducted to identify the relationship and find the best result. Three models were used to predict SCRIM values using other road features: Linear Regression model is used as a baseline model, Support Vector Regression and Random Forest Regression is used as robust machine learning algorithms. A cross-validation approach is performed to ensure result accuracy and model stability.

The modelling process aims to determine whether the SCRIM values can be predicted accurately. Moreover, the most crucial part is identifying the most relevant factors affecting the SCRIM model. The feature importance technique will be used to accomplish this. SHAP (SHapley Additive exPlanations) (Lundberg & Lee, 2017) feature importance was used to determine the significant factors. A large absolute SHAP value can determine the important features of the model. Such information can be used to determine a suitable SCRIM testing site and for further investigation.

3 Results and Discussion

3.1 Modelling Result

The Linear Regression Model 1 shows that The correlation between SCRIM and Texture for each of the three surface types was close to 0, indicating that a linear model is not suitable for our task of predicting SCRIM from texture values. The low Pearson correlation coefficient (R) and coefficient of determination (R^2) also indicated a minimal correlation between these two variables.

The best performing model is the Random Forest Regression Model, and Table 1 shows the model results. Compared to the baseline and other models, this model performed better in predicting the SCRIM coefficient value in three surface types. Particularly, the model is capable of predicting well for Open Graded Asphalt. Achieving a good determination coefficient (R2 = 0.82), low Root Mean Square Error (RMSE = 2.46) and low Mean Absolute Error (MAE = 1.83). Compared with other models, the Random Forest Regression Model has a higher coefficient of determination (R^2) and lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Based on the above, Random Forest Regression is a better regression classifier for this data.

	Sprayed Seal	**Dense Graded Asphalt**	**Open Graded Asphalt**
	Linear Regression Model 1 (Two variables)		
R	0.31	0.03	0.20
R^2	0.09	0.001	0.04
	Linear Regression Model 2 (Baseline Model)		
R^2	0.42	0.26	0.54
RMSE	9.70	5.21	3.90
MAE	6.89	3.77	3.12
	Random Forest Regression Model		
R^2	0.61	0.48	**0.82**
RMSE	8.07	4.37	**2.46**
MAE	5.47	3.14	**1.83**

Table 1 Model performance evaluation table

3.2 Feature Importance

Figure 1 shows the feature importance bar plots for the three surface types (Sprayed Seal, Dense Graded Asphalt and Open Graded Asphalt) for the best performing model Random Forest Regression. It can be seen that the most influential factor in predicting Sprayed Seal SCRIM coefficient value is Region Information. Compared with other features, Region 1 and 5 (Greater Southern Region and Goldfields Esperance Region) contribute significantly to SCRIM prediction. The other significant contributor factors are Annual Average Daily Traffic, Lane, Speed Limit, Climate Zone and Texture; For Dense Graded Asphalt, Texture, Speed Limit, and Annual Rainfall all significantly affect the prediction of SCRIM. The other significant contributor factors are Lane, Annual Average Daily Traffic and Surface Material; For Open Graded Asphalt, the figure shows that the Annual Average Daily Traffic is the major contributor to predicting the SCRIM coefficient value. Lane, Texture, and Annual Rainfall also contribute significantly. Accordingly, all of the above factors have a large absolute SHAP value compared with other features, which indicates their importance.

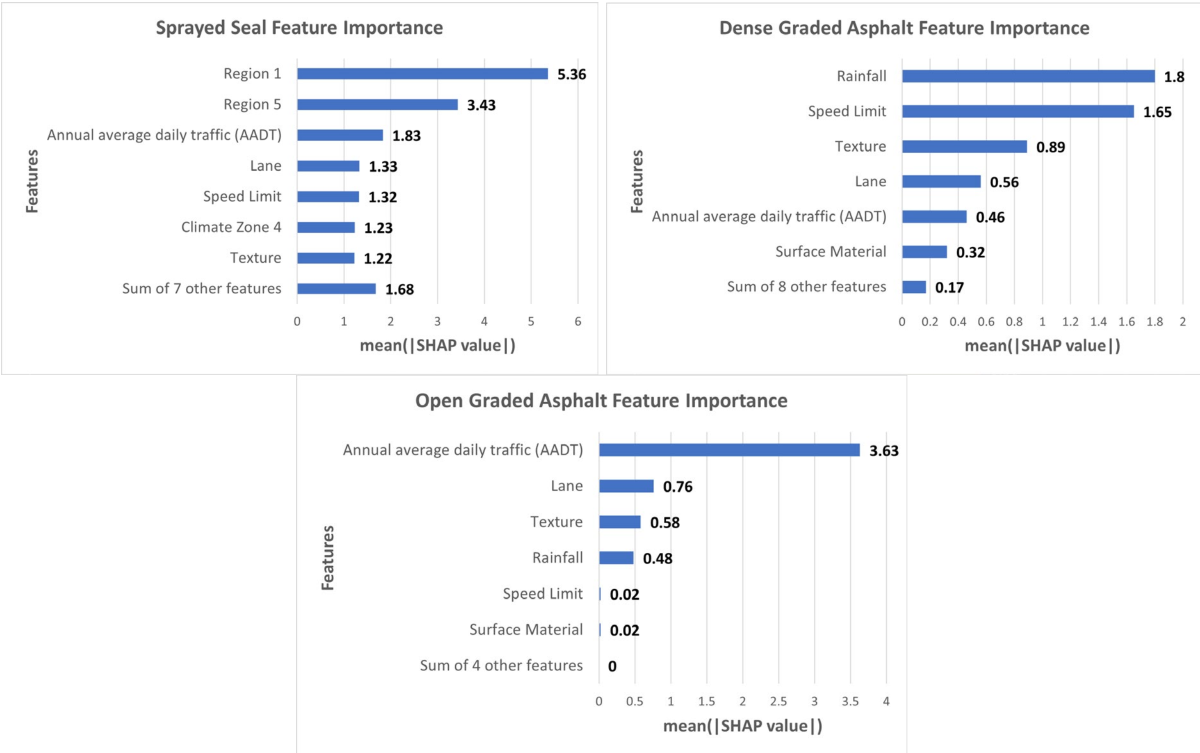

Figure 1 Feature Importance of Three of the Random Regression Models based on Surface Type

Table 2 summarizes the important features across the three road surface models. In general, Texture Depths, Annual Average Daily Traffic, Lane, and Speed Limit appear to be influential factors in predicting SCRIM across three surface types. In addition, Annual Rainfall and Surface Material were important factors in predicting SCRIM values for asphalt. Sprayed Seal SCRIM value was influenced by Region information and Climate zone. A similar study has also found the above factors influential in SCRIM (Pérez-Acebo et al., 2020).

Factor	**Sprayed Seal**	**Dense Graded Asphalt**	**Open Graded Asphalt**
Region Information	✓	✗	✗
Texture Depths	✓	✓	✓
Annual Rainfall	✗	✓	✓
Surface Material	✗	✓	✓ (Small effect)
Annual Average Daily Traffic	✓	✓	✓
Lane	✓	✓	✓
Speed Limit	✓	✓	✓ (Small effect)

Table 2 Table of factors that influence model predictions

4. Conclusions and Future Work

This project has explored how data analysis and research can be conducted using different datasets collected by Main Roads. Based on the statistical analysis, the correlation between SCRIM and Texture is low. Furthermore, the modelling part has demonstrated the possibility of using texture with combined other features for SCRIM prediction. The influence factors on SCRIM prediction were extracted with the feature importance process. Variables that truly influenced SCRIM prediction were Texture Depths, Annual Average Daily Traffic, Lane and Speed Limit. Additionally, different types of Surface Materials are affected by different factors, but in general, they share most of the influencing factors. All this information could assist Main Roads in targeting and locating potential zones that would refine the risk management and data collection process.

Future work will focus on integrating and experimenting with other potential variables related to this topic to fine-tune the model performance and gain more understanding of other factors that might affect skid resistance. The study can include more comprehensive information about road geometry in the future.As SCRIM data is recorded at a more detailed interval (5-meters), in order for the data to be integrated with Texture Depths (100-meters), the number of records has been reduced to nearly 1/20 of its original number. The valuable SCRIM data could be fully utilised if Texture Depths were recorded at a smaller or equivalent interval. Future research may also explore and analyze other variables, such as age, polished stone value, and type of carriageway, proposed by other studies (Pérez-Acebo et al., 2020).

5. Acknowledgements

My deepest gratitude goes out to many involved in this project. These included my supervisor, Prof. Rachel Cardell-Oliver, and Prof. Yuxia Hu, who gave me invaluable guidance and support. Additionally, I would like to thank my mentor, Simon Beard, and other Main Roads Western Australia staff, including Steve Atkinson and Qindong Li, for their valuable advice and industry experience. I would also like to extend my thanks to Jeremy Leggoe and Kimberlie Hancock for arranging the CEED program and allowing me to be part of it.

6. References

Cairney, P., & Bennett, P. (2013). *An exploratory study of surface characteristics and crash occurrence on selected roads in Australia* (Issue ARR 382). https://trid.trb.org/view/1259293

Davies, R. B., Cene, P. D., & Henderson, R. J. (2005). The effect of skid resistance and texture on crash risk. *Proceedings Surface Friction Roads and Runways, Christchurch,* 1–4.

Lundberg, S. M., & Lee, S.-I. (2017). *A Unified Approach to Interpreting Model Predictions.* Neural Information Processing Systems; Curran Associates, Inc. https://papers.nips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html

Pérez-Acebo, H., Gonzalo-Orden, H., Findley, D. J., & Roji, E. (2020). A skid resistance prediction model for an entire road network. *Construction and Building Materials, 262,* 120041. https://doi.org/10.1016/j.conbuildmat.2020.120041