Aurora

working to advance road weather information systems technology

Optimal RWIS Sensor Density and Location – Phase III:
Continuous Mapping of Winter Road Surface Conditions via Big Data and Deep Learning

tech transfer summary

The researchers developed a systematic, yet transferrable, method for estimating key road surface condition variables between road weather information system stations using large-scale data and two advanced modeling techniques—kriging and deep learning.

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The Aurora program is a partnership of highway agencies that collaborate on research, development, and deployment of road weather information to improve the efficiency, safety, and reliability of surface transportation. The program is administered by the Center for Weather Impacts on Mobility and Safety (CWIMS), which is housed under the Institute for Transportation at Iowa State University. The mission of Aurora and its members is to seek to implement advanced road weather information systems (RWIS) that fully integrate state-of-the-art roadway and weather forecasting technologies with coordinated, multi-agency weather monitoring infrastructures.

The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the project partners.

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Problem Statement

Estimating road surface condition (RSC) has long been recognized as a challenging task, while it is essential in optimizing winter road maintenance (WRM) operations.

Background

The monitoring and estimations of RSCs play a critical role in optimizing WRM activities. In recent decades, road weather information system (RWIS) technologies, both stationary and mobile, have gained popularity with many road maintenance authorities and become a predominant intelligent transportation system (ITS) technology. While RWIS technologies provide real-time and near-future RSC information that is critical in making timely maintenance related decisions, RWIS technologies are relatively expensive to maintain and operate and are therefore only installed at a limited number of locations.

The limited number of RWIS stations along with the need to monitor spatially large road networks with vastly varied conditions necessitate a strategic and scientific approach to the continuous and accurate monitoring of RSCs during inclement weather events. Furthermore, most RWIS stations nowadays are equipped with cameras that provide users with a direct view of the RSCs; however, the process of classifying RSCs using these camera images is still being done manually. If this process can be automated, transportation agencies will be able to use the rich image-based road condition data more effectively and, in turn, improve the level of service that they provide.

Goal and Objectives

To tackle the foregoing challenges and provide solutions to better serve the public and road authorities, this project aimed to develop a methodological framework for estimating winter RSCs and to automate the process of image recognition to fill in the spatial gap of unmonitored areas using RWIS and other sensing technologies.

Research Description

To evaluate the feasibility and reliability of the proposed methods, a case study was conducted by selecting several highway segments from Iowa, where a comprehensive geodatabase was constructed by incorporating the historical observations of RSC variables, weather conditions, and vehicle-mounted dash camera images collected by the Iowa automated vehicle location (AVL) system from October 2018 through April 2019, as well as the geographical and topographical features of each highway stretch.

As a result, a hybrid geostatistical model, regression kriging (RK), was developed by incorporating two conceptually different models to map spatial variability and strengthen the explanatory power of key RSC variables, which included the road surface temperature (RST) and road surface index (RSI), representing road slipperiness.

Semivariogram modeling was also involved in the RK to investigate the spatial variations of target variables. In total, the researchers developed 228 and 34 semivariogram models for RST and RSI, respectively. These two variables were also utilized to evaluate the feasibility of RK by conducting cross validations.

A deep learning (DL) model was developed to automate the process of RSC image recognition.

As previously mentioned, RSI was one of the RSC variables that were used in the development of the RK method. It is a friction-like surrogate measure used as a numerical indicator for the overall RSC. RSI itself is not directly collected at the AVL, but is instead converted from the RSC category classified by the trained DL model prior to RK interpolation. To make the converted RSI more representative, an image thresholding technique was used to further adjust the RSI values for images labeled with the same RSC category. Converted RSI values were then used as input in the RK method for RSI interpolation.

In addition to estimating RSC variables, it is also important to understand the relationship between spatial variation patterns of the variables and the underlying meteorological factors, which can be used as priori knowledge or fingerprints for implementing RK without the need to send personnel to collect data before making decisions on WRM activities.

The nugget-to-sill ratio (NSR) obtained from the semivariogram model of a target variable represents the spatial dependence of the variable and, therefore, can be used to characterize the spatial dependence of the RSC. This NSR value can vary depending on the weather event. Based on the literature review and other available data, wind and rainfall were used in this study to examine potential correlations between RST and wind and rainfall weather events. All variables relating to wind and rainfall were aggregated into the three NSR classes (i.e., spatial dependence classes). Due to the lack of data, an analysis pertaining to RST was only included in this portion of the analysis.

Finally, the developed solutions were integrated into a HyperText Markup Language (HTML) based visualization application to demonstrate the robustness of the proposed method and the resulting estimations between RWIS stations.

Key Findings

Through cross validation, the estimated RSC variables (i.e., RST and RSI) using RK showed excellent results, confirming the feasibility of the proposed method. With as few as one point measurement as input, RK can well capture the general patterns of the RSC along a stretch of highway. The researchers also found that the estimation quality depends on the density of the RWIS network. They found that the accuracy of the developed model improves when the number of point measurements increases. This was further supported by kriging estimation variance, where it decreases with the addition of more RWIS stations, meaning the reliability of the model's predictions improves with the number of stations.

Contrary to this pattern, some hourly events showed that estimation errors (i.e., RMSE) did not decrease with an increased number of input point measurements, which can be attributed to different weather events affecting the RK interpolation accuracy, as it is not typically uniform over space or time. This also suggested that an optimal placement strategy for RWIS stations is needed to account for both local and regional weather characteristics.

The developed DL model was shown to be highly accurate with training and validation accuracies being 99.89% and 94.62%, respectively. The confusion matrix, which shows the performance of the DL model in terms of both false positive and false negative measures, also affirmed that the model can successfully distinguish between the different RSC categories. The validation accuracy for each category was over 90%, suggesting that the DL model is a practically applicable approach for determining RSC from dash camera images.

However, the researchers found limitations to this DL model, in that it is constructed with a relatively simple architecture fit only for this project's specific purpose. It was also highly dependent on image quality given that images with extraneous elements tend to not be accurately classified.

Furthermore, weather events can be characterized by RST using the NSR. Overall, strong wind and heavy rainfall tended to create a stronger spatial dependence of RST in the study area. This result can help in understanding the correlation between the RST variation pattern and meteorological factors, which can also be used as priori knowledge for a more efficient RK interpolation and decision-making process for WRM activities.
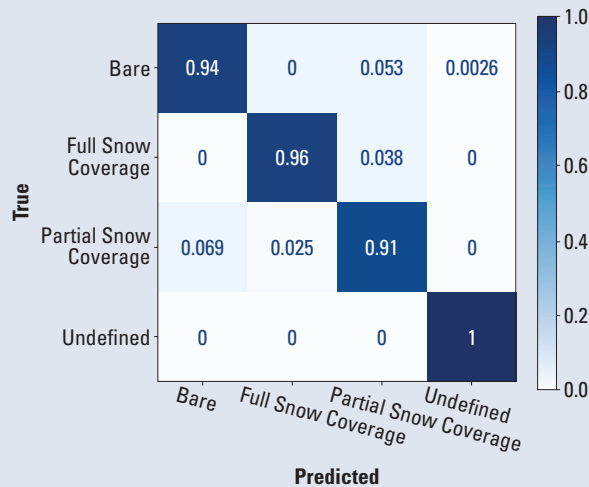
Confusion matrix

Deep Learning Model Performance

The number of correct and incorrect predictions are summarized with normalized values (i.e., percentages) and are broken down by each category: bare pavement, partially snow covered, fully snow covered, and undefined. The values in the diagonal line of dark-shaded squares from upper left to lower right represent prediction accuracy, while the remaining values in the lighter-shaded squares in each column represent the false positive rate (FPR) (where DL predictions are positive but they are false/incorrect predictions) and the values of each row represent the false negative rate (FNR) (where DL predictions are negative but they are false/incorrect predictions).

For example, in the first row of the confusion matrix, 0.94 means the DL model correctly classified 94% of new bare pavement images into the bare category, but incorrectly classified 0% (0), 5.3% (0.053), and 0.26% (0.0026) of them into the other three categories, and the summation of these three values is called the FNR. For other non-bare images, the DL model incorrectly classified 0% (0), 6.9% (0.069), and 0% (0) from each category to the Bare category, and the summation of these three values is called the FPR. High prediction accuracy with a low FNR and FPR implies an accurate DL model.

Implementation Readiness and Benefits

Using the techniques presented in the final report for this project, transportation agencies can expand their RSC spatial coverage substantially, enhancing their ability to perform WRM activities faster, more efficiently, and more cost-effectively, and ultimately provide the general public with a greater level of service in terms of winter traffic safety and mobility.

Future Research Recommendations

In terms of future research, it is necessary to expand the case study area to cover more highway sections with varying orientations (e.g., north-south and east-west routes) to further validate the proposed RK method, and to better generalize the weather characterization results. Additional variables, such as meteorological factors, geographical and topographical factors, and traffic parameters (e.g., traffic volumes) can be added into the analysis to minimize their potential confounding effects on the RSC.

To improve the generalization of RSC image recognition, more advanced DL models (e.g., ResNet-50) can be adopted to improve RSC image recognition performance. In addition, more RSC categories can also be considered to further distinguish the differences between road surface slipperiness. Other computer vision or image processing techniques can also be developed and applied to convert each RSC image or RSC category into finer RSI values. Furthermore, the development and inclusion of better image technology, such as thermal camera overlays, have the potential to further improve RSC monitoring and estimation results.

Lastly, to better aid the decision-making process for WRM activities, the application of the RWIS location optimization method can be further extended to determine the optimal number of new RWIS stations required. Their corresponding optimal locations should also be considered by running multiple simulations and incorporating various objectives (e.g., traffic monitoring), weather events, and specific local attributes.