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Road Surface temperature forecast. The statistical insight

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ABSTRACT

Thermal mapping has been implemented since the late eighties to determine road ice susceptibility. It consists in measuring road pavement temperature along with some other atmospheric parameters to build a winter risk. Measurements are done using a vehicle embedded into the traffic in given road weather conditions. If the dew point temperature is lower than road surface temperature there is a risk of ice occurrence, and therefore a loss of grip for circulating vehicles. Road surface temperature is obtained with an infrared radiometer on board of a dedicated vehicle. Thermal mapping is usually done before dawn during wintertime in specific weather conditions, when the energy accumulated by the road during daytime is mainly dissipated and before the road structure starts a new thermal cycle. Measurements are anyhow time-consuming. A whole road network can hardly be analysed at once. So far, thermal fingerprints were either used directly to identify the susceptibility to ice occurrence of routes, or as an input to forecast road surface temperature with physical numerical models. These models are based on an energy balance description, and needs an accurate knowledge of both meteorological and road parameters. The objective of this work is to present how an approach based on multivariate data analysis was implemented to thermal mapping. The objective was to gather a given number of thermal fingerprints, with road surface temperature and air temperature at least, and in weather conditions representative of winter. Then data was processed through partial least-squared regression to establish a statistical forecast model for road surface temperature. Results obtained on a whole route provided a forecast with an error similar to the one of physical numerical model. Its application to specific zones could ease the forecast, reduce computation time, and provide an increasing role to thermal mapping.

Keywords: thermal mapping, PLS, winter maintenance.

1 INTRODUCTION

Thermal mapping remains a key winter maintenance tool, dedicated to identify ice susceptibility along routes. Measurements of road surface temperature (RST) and other atmospheric parameters are used to build an indicator to ice occurrence [1-10]. Data can also be used in physical numerical models to RST. If the dew point temperature is lower than road surface temperature, there is a risk of ice occurrence, and a loss of grip for circulating vehicles could occur. Instruments, vehicle and monitoring conditions used for thermal mapping were previously detailed in the literature [10, 11, 12]. The analysis of the thermal data collected helps road network managers to monitor specific dangerous locations through road weather information systems installed on specific spots identified thanks to thermal mapping, or to install road signs. If measurements are considered as time consuming, thermal mapping data is so far used as an input in numerical model dedicated to RST forecast. The purpose of this study was to use thermal mapping vehicle and its data as the core of a RST forecast based on a statistical analysis, approach jointly started with the University of Birmingham. The forecast is based on principal components analysis (PCA) and on partial least-square (PLS) regression specifically. A route covering a wide range of configurations was monitored over several months in various weather conditions and in different seasons. Air temperature, relative humidity and surface temperature were recorded at a 3-m spatial frequency. Data collected was analysed through PCA and PLS to identify the minimum required number of samples. Results of PLS have shown that the PLS model could have a R^2 of 0.9562, a root mean square error in prediction (RMSEP) of 1.87 and a bias of -0.66. The same model applied to establish a forecast on known event indicated an average difference between measurements and forecasts as low as 0.30°C.

2 THERMAL MAPPING MEASUREMENTS

The University of Birmingham, and DTer Est Nancy site of the CEREMA have been collecting thermal mapping data early after the technique appeared. The French vehicle is illustrated and detailed elsewhere in the literature [10-12], and is now equipped with cost effective sensors with appropriate performances, detailed in Table 1. All parameters are measured simultaneously on the vehicle to ease future data treatments.

The infrared radiometer is a PS 12 AF1 model from KELLER, mounted on the front bumper of a car, in a compartment which temperature is regulated around 18°C. The compartment is located at about 40 cm above the road surface. Usual atmospheric parameters such as air temperature, relative humidity were monitored also recorded. Measurements were obtained with a SHT15 model from SENSIRION located in a structure lo have the sensor in a laminar air flow.

Infrared radiometer	
Detector type	thin film thermopile
Spectral bandwidth	8-14 µm
Thermal range	-30°C to + 70°C
Repeatability	1 K at air temperature constant and ε=1
Measuring uncertainty	1.5 K (-10°C to +40°C, at an air temperature of 23°C and for ε=1)
Area of measurement	35 mm of diameter at a distance of 40 mm
Time response	< 150 ms
Temperature coefficient	0.1 K/K deviation at an air temperature of 23°C within a temperature range of +10°C to +40°C
Atmospheric probe	
air temperature range	-40°C - 125°C
air temperature accuracy	±0.3°C
air temperature response time	from 5 to 30 s
relative humidity range	0% - 100%
relative humidity accuracy	±2%
relative humidity response time	8 s

Table 1. Characteristics of infrared radiometer and atmospheric probe of the thermal mapping vehicle.

As indicated in a previous communication [12], the chosen route for the test was tens of kilometres long. It included several configurations, from single lane road to multiple lanes highway, passing above and below bridges, with and without roadside trees, and across agglomerations. Measurements were run in various weather conditions, from a clear sky and up to total cloud cover, and a large panel of temperatures, at different seasons of the year. On highways, the vehicle remained in the right lane. A large distance with preceding vehicles was maintained to avoid their thermal signature. Tens of thermal fingerprints were then collected.
RST profiles are more or less constant, with an offset due to local temperature, local distortions, and environment heterogeneities (Figure 1). As previously indicated, a generic thermal fingerprint of this itinerary was identified.

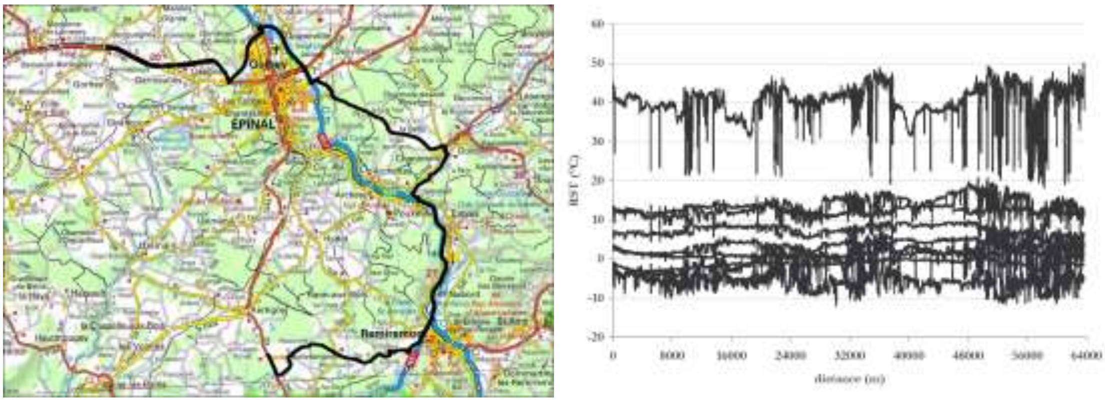

Figure 1. Map of chosen route and associated thermal fingerprints.

3 PCA AND PLS ON THERMAL FINGERPRINTS

3.1 Principal component analysis results

This statistical tool uses the variance-covariance matrix. Linear transformations of a group of correlated variables are obtained in such a way that certain optimal conditions are met. The transformed variables are located in a new mathematical space, and uncorrelated. The physics that generates the variations is "lost" for a mathematical one. The number of initial variables involved in the description of the physical phenomena resulting in thermal fingerprints is reduced to a lower number called principal components. The data is then projected into the space of the so-called principal components built on the linear combination real physical factors. Calculations are meant to identify the space gathering the highest variance. PCA is a descriptive one, based on a NIPALS ("Nonlinear estimation by Iterative Partial Least Squares") algorithm. [13, 14].
Data from several thermal surveys was used to generate a matrix. The matrix has as many lines as thermal fingerprints, and as many columns as distance points where measurements were performed. Each thermal fingerprint will therefore correspond to one point in the PC space. A set of thermal fingerprints of the whole route was used to run a principal components analysis, and identify specific samples. As expected, explained variance reached 98% with one principal component, and the summer thermal fingerprint is very specific with respect to other ones (Figure 2).

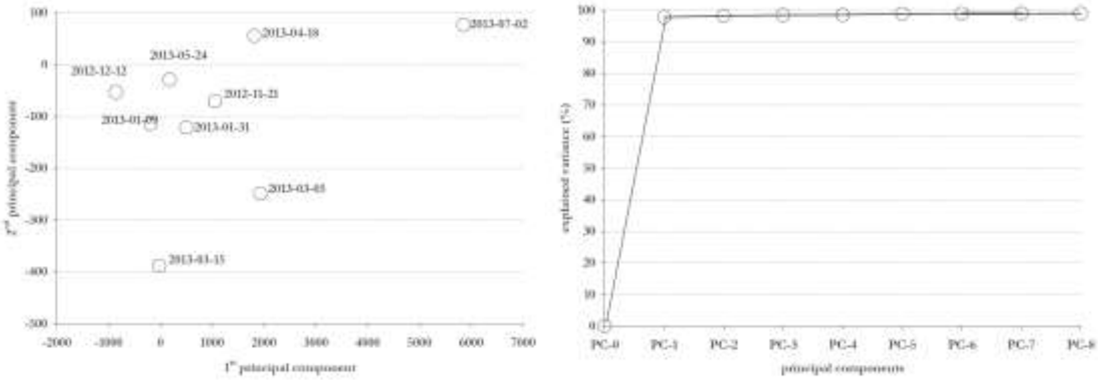

Figure 2. Results of principal components analysis on thermal fingerprints of the route.

3.2 Elaboration of the statistical forecast model

The main issue in winter maintenance is to obtain a reliable and cost effective forecast of RST. The work suggests an approach in which thermal fingerprints, rather than numerical models, are used to drive the forecast. The approach would solve the issue of the poor knowledge of road structure, the choice of weather conditions and time when thermal fingerprints are performed, and the questionable performances of infrared radiometers. The performance of the statistical model was analysed through R^2 and RMSE output values. The statistical forecast model based on Partial Least-Square regression (PLS) applied to thermal mapping data, with air temperature as the sole variable. This choice is based on the facts that air temperature measurements are well

established both by world meteorological organization (WMO) and by standards dedicated to road weather information systems.
PLS was run with Unscrambler X 10.1 software with mean centred data, using NIPALS algorithm, with cross validation, of a set of 7 thermal fingerprints.
Data was first fully used without any treatment, then using one column out of 12, and finally using a filter on RST data. In all cases, computation time did not exceed one minute on a conventional computer. Results are summarized in Table 2, in the case of a statistical description using five principal components, with seven samples.

PLS case	*R^2*	*slope*	*offset*	*RMSEP*
all data	0.9415	0.857	-0.15	1.46
one column out of 12	0.9219	0.822	-0.16	1.72
Gauss filter on RST data	0.9480	0.872	0.21	1.31

Table 2. Results of PLS forecast model.

Results of the forecast statistical model built with 7 thermal fingerprints, using a gauss filter on RST data are summarized on Figure 3. They indicated that RST could be determined with a good degree of confidence with the sole use of air temperature. Similar results were obtained using only five samples.

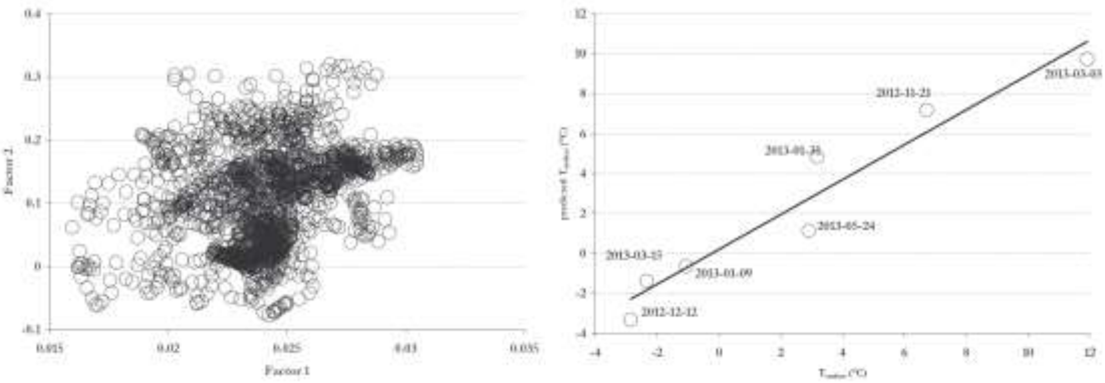

Figure 3. Results of PLS calculations with loadings distributions (left) and forecast model (right).

3.3 RST forecast

Once these calculations were performed, the objective was first to establish to which extent a RST determination could be established on the basis of on air temperature measurement. Then, the work consisted in using such approach to build a RST forecast.
To do so, a PLS model was elaborated with RST and air temperature data. Then using another air temperature profile along the same route, which range was within the one used in the elaboration of the PLS model, the predicted RST profile was calculated. A comparison was then made with RST measurements obtained with the air temperature.
The PLS model was established with six thermal fingerprints and six corresponding air temperature profiles. The RST covered range was between -3°C et 11°C. Average RMSEP average the route is of 1.87 with the best description involving three principal components (Figure 4). The application of the model to an air temperature profile provided a corresponding RST profile. Calculated and measured thermal fingerprints are given in Figure 5. Results indicated the ability of a PLS model to provide a good result, with an error similar to usual numerical model, and without needing any specific knowledge of the infrastructure or weather conditions. The most interesting aspect will be to run a calculation of the PLS model with a forecast of the air temperature profile instead of measured one, to elaborate a forecast of the corresponding RST. Such approach could also be routinely available. Indeed, cars have now temperature sensors and the concept of dialogue between an infrastructure and circulating vehicles has now been implemented. It would then be possible to statistically forecast RST on this basis, and use thermal mapping to generate initial model.

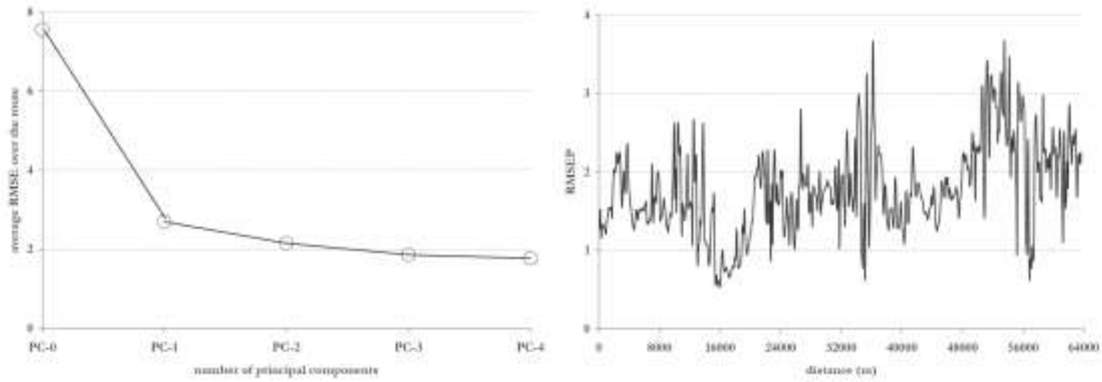

Figure 4. PLS model characteristics used for RST determination

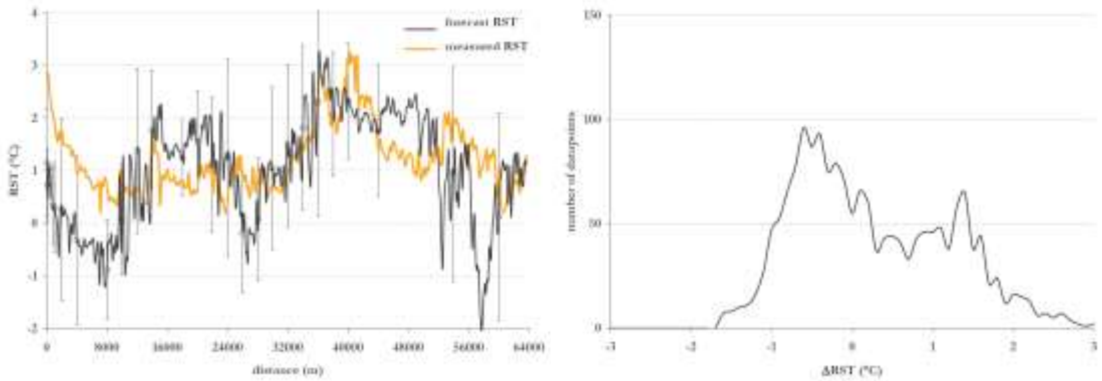

Figure 5. Comparison between RST determined by a PLS model and measurements, along with errors.

4 CONCLUSION

Thermal fingerprint helps roads network manager to identify specific dangerous locations for their future monitoring through road weather information systems. The purpose of this study was to use thermal mapping vehicle and its data to elaborate a RST forecast based on partial least-square (PLS) regression. A route covering a wide range of configurations was monitored in various weather conditions and seasons. Atmospheric parameters and RST were recorded, and analysed through PLS, with a minimum set of 5 samples. Results of PLS have shown statistical model built with PLS could provide a good RST forecast. The same model applied to establish a forecast on known event indicated an average difference between measurements and forecasts as low as 0.30°C. This result for a full route could be improved considering more parameters than the sole air temperature as a predictor, and reducing the spatial scale to route sections such as bridges or wood areas.

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