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Optimize pavement monitoring using artificial intelligence (Roadcare)

#ICA4point0

Antonin MANCEL (Roadcare), France
antonin.mancel@roadcare.ai

Tien Sy NGUYEN (Roadcare), France,
tien-sy.nguyen@roadcare.ai

Nuria UGUET CANAL, (EUROVIA), Spain,
nuria.uguet@eurovia-es.com

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1. INTRODUCTION

Efficient management of road assets involves prioritising and planning the maintenance operations to be carried out. This technical and financial management must be supported by feedback from the field on the condition of roadways.

Even today, for secondary road network, these field reports are essentially based on visual inspections, with the subjectivity and difficulty of reproducibility that this implies.

While conventional inspection methods are regularly used to characterise the main road network, they are rarely used on "ancillary" pavements - not least because of their cost.

Consequently, large-scale, objective characterisation adapted to the "ancillary" network is a difficulty faced by many private and public managers.

Significant progress has been made in recent years in research into the automatic detection of defects on pavement images, thanks in particular to AI with a deep learning approach (Maeda et al, Ottoni et al, Bharat et al, FUJII et al), and new inspection solutions using on-board cameras and Artificial Intelligence are flourishing on the market.

While these innovative solutions offer a new opportunity for asset managers, their adoption raises several questions, including:

- How can the multitude of data produced by AI be synthesised in a way that is relevant from a business point of view?
- How can we ensure continuity with existing indicators?
- Is it possible to guarantee the interoperability of the output data with the software solutions already deployed by managers (GIS, RIS, etc.)?

Based on its experience of different types of asset, from motorway rest areas to pavements and secondary roads, Roadcare presents a global methodology for processing data derived from Artificial Intelligence applied to the field of road diagnostics.

2. CONTEXT AND OBJECTIVE

2.1 Roadcare: an innovative road engineering solution from DIAGWAY

Roadcare, the new commercial brand of the VINCI Group's DIAGWAY road engineering division, has developed a solution tailored to managers of secondary networks, for which conventional inspection methods often appear to be oversized from a technical and economic point of view.

The idea is to use a simplified acquisition system (Smartphone, GoPro, DashCam, Drone) to build a complete solution enabling road network managers to optimise the monitoring and maintenance of their pavement assets.

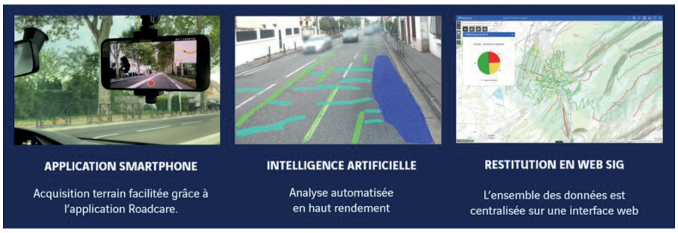

Figure 1 - How the Roadcare solution works: simplified Smartphone acquisition, automated Artificial Intelligence damage survey and GIS web platform for reporting and decision support.

2.1. Methodology objective(s)

Based on the elementary data produced by Artificial Intelligence, the objective was to define a robust, configurable and operational indicator for the road manager.

This indicator will form the bridge between the raw data output by AI and the high added-value summary information.

Here are the success criteria set for the definition of the indicator:

- Reliable from a business point of view, i.e. close to what is felt, it being understood that, when it comes to characterising the state of the road, it is commonly accepted that there is a ceiling of around 80% convergence between experts.
- Customisable: the indicator must be adaptable to the local context: habits in terms of rating, maintenance strategies, etc.
- Robust: a non-significant variation in the input data, or in any assumption of the overall process, must have a reasonable impact on the final indicator.
- Interoperable: the indicator can be fed by external data (HGV traffic, physical measurements) or, conversely, it must be able to integrate an existing database.
- Transparent: the indicator will be associated with a reliability index, to enable the user to prioritise quality control after the event if necessary.

3. METHOD FOR CHARACTERISING THE CONDITION OF ANCILLARY CARRIAGEWAYS: EXAMPLE OF A REST AREA STUDY

3.1 Course of the assignment

- Appropriation of the customer's reference system
- In situ acquisition
- Pre-processing of data
- Defects inventory using Artificial Intelligence
- Quality control of results
- Export in GIS format
- Post-processing: calculation of indicators by sub-area
- Comparison of diagnostic results with customer perceptions
- Possible adjustments to indicators to bring them closer to customer perceptions

3.2 Appropriation of the customer repository

The customer database forms the basis for asset management. In the case of rest areas, the reference system was surface-based and each site was divided into a study sub-area.

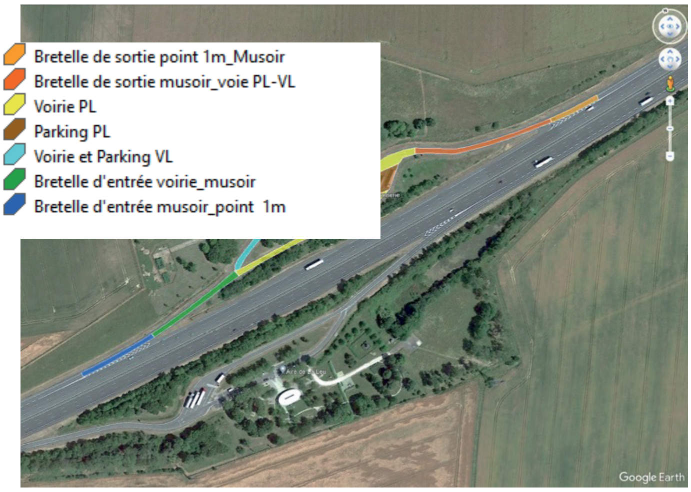

Figure 3 - Illustration of the zoning of the sites studied.

3.3 In situ data acquisition

The survey is carried out in a vehicle equipped with a smartphone and the Roadcare application.

The geo-referenced videos collected in this way, known as "sessions", are then imported into the web interface.

Figure 4 - Inside or outside installation

The inspection is carried out in the flow of traffic, at "normal" speed: no disruption to traffic is to be expected.

In a single pass, the application collects 1920 x 1080-pixel resolution photos with curvilinear distance and GPS coordinates.

Figure 5 - Illustration of the Smartphone acquisition application

3.4 Data pre-processing

Once on the servers, the videos are extracted to images, one image for each 5 meters,. Calibration is then performed on an image showing a reference checkerboard - or any other surface object of known dimensions.

Figure 5 - Illustration of the Smartphone acquisition application

Figure 7 - Illustration of the calibration tool on a pedestrian crossing of known dimensions - a reference object commonly used by default as a checkerboard.

3.5 Artificial Intelligence based Road defects survey

The inventory of defects will be facilitated by our Artificial Intelligence algorithms.

The Roadcare defects catalogue is based on the deteriorations defined in LCPC Test Method ME 38-2, then adapted to computer vision methods, typically by merging subjective criteria that are difficult for AI to discern.

Below are two examples of automated detection.

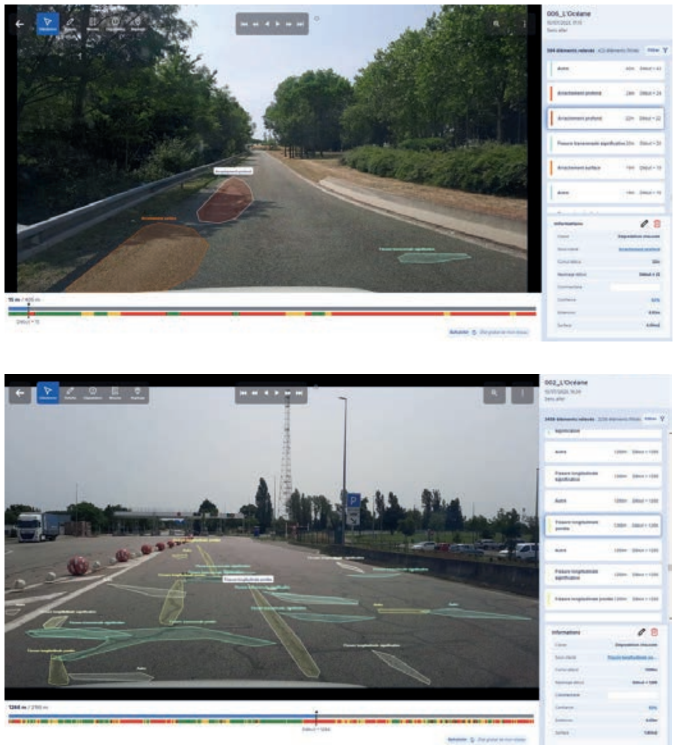

Figure 8 - Illustration of Artificial Intelligence analysis using the Roadcare Segmentation model.

3.6 Quality control of results (optional)

Once the analysis has been completed, a quality control check is carried out to define the optimum confidence thresholds for each type of degradation.

The aim is to put the cursor in the right place so that the model detects as many defects as possible that are actually present, and as few false positives as possible, in order to filter out, for example, the shadow of a lamppost perceived as a bridged crack.

3.7 Export to GIS format

In order to obtain better geo-referencing of the damage, it is recommended to re-align the GPS trace for areas with a lot of masking (buildings, trees, etc.).

Each item of damage is then exported to the GIS. The surface areas of elementary damage are summed up by type and by elementary mesh (5m*5m square).

In order to avoid counting several times the damage detected in several images of a single or several passages, we merged the damage geometries by type before calculating the distribution of each type of damage by elementary mesh.

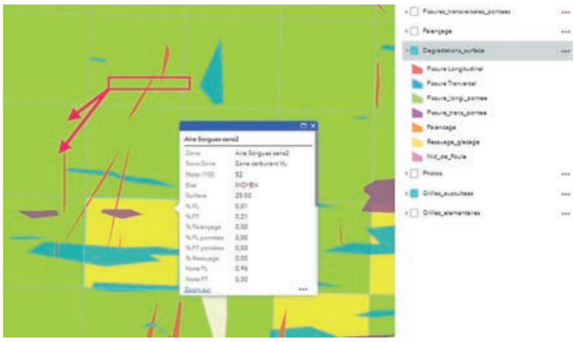

Figure 9 - Illustration of degradations recorded by AI exported to the GIS.

3.8 Post-processing: calculation of indicators by sub-area

A "maximum" threshold is determined in order to maintain the widest dynamic range of ratings. For example, above 30% of cracked surface, the "cracks" criterion will be given the lowest score, i.e. 0.

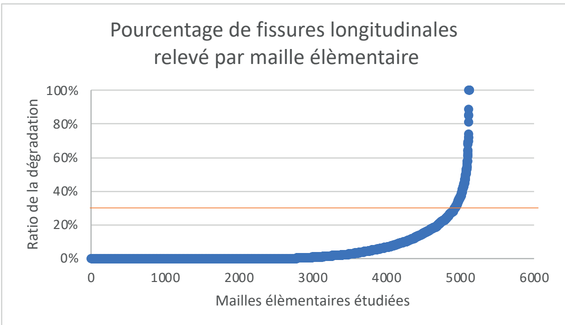

Figure 10 - Illustration of the ratio of degraded surface area per elementary grid cell.

For each elementary grid cell, a score per defect is calculated according to the following formula:

Degradation_note = 1 – min [(Defect_area/ Elemental_area) / Maximum¬Defect-Criterion]

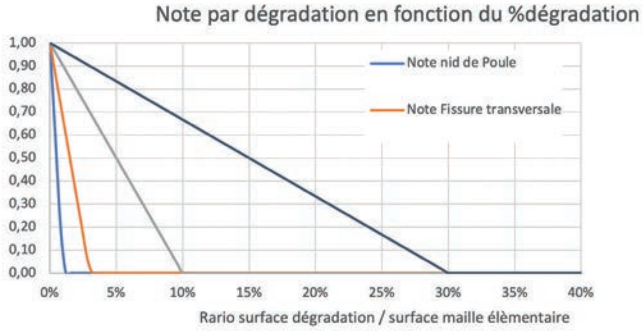

Figure 11 - Illustration of the grade per defect as a function of % defect

The score is then weighted by a power coefficient according to the importance we wish to give to the defect class in the overall score:

Weighted score = Gross_score ^ Coefficient

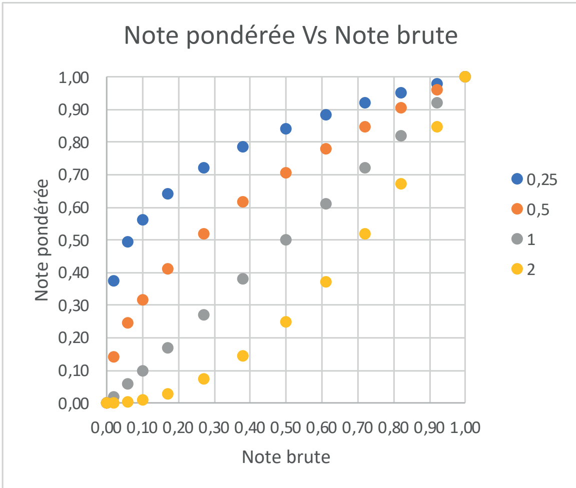

Figure 12 - Illustration of the raw Vs weighted degradation score

Next, an overall score is calculated for each elementary mesh by multiplying each weighted score:

Overall_Rating = Product of Defect_Rating ^ Defect_Coefficient

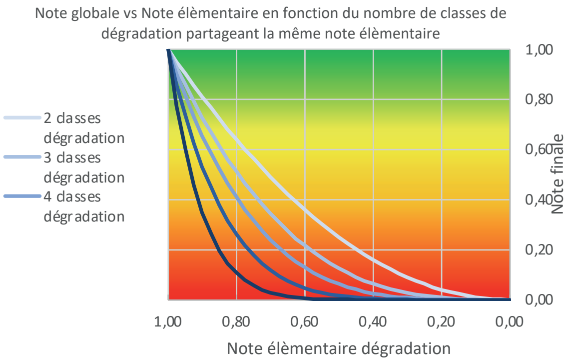

Figure 13 - Overall score vs. elementary score as a function of the number of defect classes sharing the same elementary score

Finally, thresholds are associated with the objectives set by the manager. By default, we can consider:

- If the score is > 0.66→ GOOD
- If the score is between 0.33 and 0.66→ AVERAGE
- If the score is < 0.33→ POOR

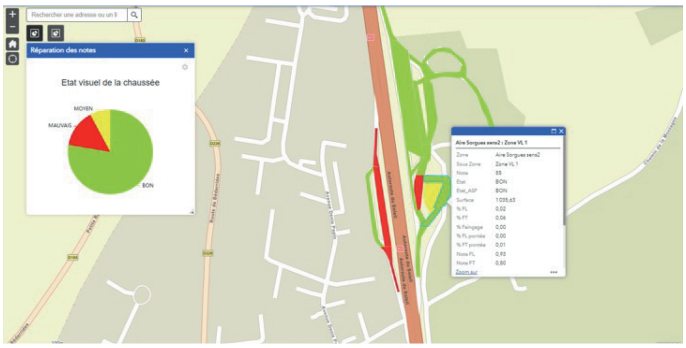

Figure 14 - Overall score by sub-area.

3.9 Comparison of diagnosis vs. manager's assessment

For each of the sub-zones studied, the diagnosis of the overall condition obtained by the Roadcare methodology was compared with the manager's assessment.

The results were 76% in agreement.

Note Roadcare	Indicateur Roadcare	Ressenti	Ecart	ABS(Ecart)
0,15	MAUVAIS	MAUVAIS	0	0
0,00	MAUVAIS	MAUVAIS	0	0
0,01	MAUVAIS	MAUVAIS	0	0
0,93	BON	MOYEN	-1	1
0,91	BON	BON	0	0
0,94	BON	BON	0	0
0,20	MAUVAIS	MAUVAIS	0	0
0,95	BON	BON	0	0
0,92	BON	BON	0	0
0,94	BON	BON	0	0
0,95	BON	BON	0	0
0,98	BON	BON	0	0
0,90	BON	MOYEN	-1	1
0,51	MOYEN	MOYEN	0	0
0,84	BON	MOYEN	-1	1
0,43	MOYEN	MOYEN	0	0
0,86	BON	BON	0	0
0,86	BON	BON	0	0
0,28	MAUVAIS	MOYEN	1	1
0,88	BON	BON	0	0
0,51	MOYEN	MOYEN	0	0
0,97	BON	BON	0	0
0,93	BON	BON	0	0
0,69	BON	BON	0	0
0,91	BON	BON	0	0
0,95	BON	BON	0	0
0,85	BON	BON	0	0
0,70	BON	BON	0	0
0,86	BON	BON	0	0
0,77	BON	MOYEN	-1	1
0,78	BON	BON	0	0
0,57	MOYEN	MOYEN	0	0
0,86	BON	BON	0	0
0,74	BON	MOYEN	-1	1
0,50	MOYEN	BON	1	1
0,83	BON	BON	0	0
0,71	BON	BON	0	0
0,78	BON	MOYEN	-1	1
0,66	MOYEN	BON	1	1
0,79	BON	BON	0	0
0,87	BON	MOYEN	-1	1
			-10%	24%

The post-processing was then modified at the manager's request to take into account his usual indicators. The concordance then fell to 71%, which means that the Roadcare indicators were optimised to tend towards perception, and that the overall methodology remains sufficiently robust to accept minor changes to the parameters.

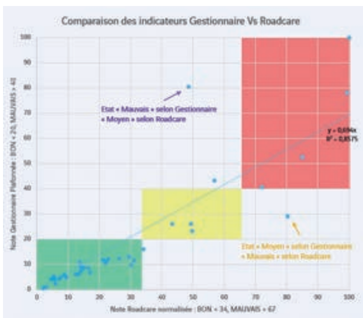

Figure 16 - Comparative illustration of the overall Roadcare Vs Gestionnaire indicator. The indicators are 86% in line.

4. CONCLUSION

Through its studies carried out in partnership with different types of public and private managers, Roadcare has been able to observe not only that the diagnosis resulting from innovative technologies using artificial intelligence allows a completely satisfactory correlation with human assessment, but also that it is entirely possible to integrate data resulting from AI as data in its own right within conventional methodologies, thus ensuring continuity with traditional visual inspection indicators.

The criteria for this success are based on several factors:

- The quality of the training data sets, which must be able to distinguish at least a dozen classes of defect with sufficient accuracy to provide robustness and flexibility in post-processing.
- The choice of an Artificial Intelligence model known as "segmentation", in order to be able to finely crop the defect detected on the image.
- Proper calibration of the image, so that metrics such as surface area or extension can be calculated for the defect detected in the image, and so that consistent, customisable indicators can be constructed.
- The quality of the GPS associated with the on-board camera, enabling the defects seen in several successive images to be cross-checked, as well as improving the accuracy of the areas scanned in several nearby traces.
- The quality of the image processing software built into the on-board camera, to reduce the effect of vibrations and changes in brightness that can degrade image quality.
- Finally, and this is one of the first conditions for success, the quality of the acquisition, i.e. on dry pavements, avoiding backlighting and reflections, favouring a slightly elevated vehicle and with a straight windscreen so as to maximise the proportion of pavement visible in the image.

When all these criteria are met, they offer the possibility of adapting post-processing with great finesse, not only in terms of the indicators calculated, but also in terms of GIS projection onto linear and surface reference frames. This ensures both continuity with existing indicators and interoperability with current business software solutions.

It should be noted, however, that this type of automated inventory is less effective when it comes to distinguishing levels of severity within the same class of defect, for example a serious or significant longitudinal crack. In fact, this distinction is relative and often contextual, making it unsuitable for systematic learning.

Adaptations may therefore be necessary to simplify standards based on this type of subjective indicator.

Finally, from a business point of view, the main limitation of methodologies based on 2D image analysis lies in the difficulty of characterising deformations such as rutting, subsidence or UNI. We therefore recommend coupling these macroscopic diagnostics with additional targeted measurements in order to be able to draw up state-of-the-art maintenance plans.

In conclusion, these innovative technologies provide an effective solution for assessing the condition of a network objectively and on a large scale, and offer a cost/accuracy ratio suited to the challenges and budgetary constraints of so-called 'secondary' network managers. They must, however, be seen as a tool - necessary but not sufficient - and be at the service of an asset management strategy steered by experts.

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