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DEVELOPMENT OF AN AUTOMATIC METHOD FOR THE RECOGNITION OF TOP-DOWN CRACKING ON ASPHALT PAVEMENTS

Davide Chiola[1], Lorenzo Paolo Ingrassia[2], Samuel Salini[1], Francesco Canestrari[2]
[1] *Movyon S.p.A., Italy*
[2] *Università Politecnica delle Marche, Italy*

Abstract

Top-down cracking (TDC) is a distress affecting asphalt pavements and consists of longitudinal cracks that initiate on the pavement surface and propagate downwards. Such a distress is critical especially for thick asphalt pavements with open-graded friction courses (OGFC), which are common on motorways and high-speed roads. Nevertheless, many road agencies are not fully aware of the TDC issue yet and thus do not have adequate tools to detect TDC. Within this framework, as part of a larger project, this study proposes an automatic method for the recognition of TDC on the pavement. The tool developed is based on machine learning (ML) algorithms and allows to identify TDC from the analysis of pavement images. The main output provided by this tool is the information on the presence/absence of TDC on the pavement, with the related confidence level. The labeling and training of the algorithm were carried out on images of a significant portion of the Italian motorway network (400 km) that were subjected to a non-automatic visual analysis in a previous phase of the project. The algorithm was then validated considering a further 100 km trial section belonging to the Italian motorway network, from which several control cores were taken. The tool developed has the potential to be used in a pavement management system (PMS) to plan timely surface repairs/maintenance against TDC, especially when combined with a model able to predict TDC depth evolution over time.

Keywords: road pavement distress, pavement management system (PMS), condition assessment, maintenance, machine learning (ML)

1 Introduction

Top-down cracking (TDC) is a distress that affects asphalt pavements, consisting of longitudinal cracks that initiate on the pavement surface and propagate downwards. TDC is basically caused by the repeated tire-pavement contact stresses, which determine the onset of tensile and shear stresses in the wheelpath area, which means that such distress is ascribable to fatigue failure (similarly to bottom-up cracking) [1-3].
Specifically, TDC is critical especially for thick asphalt pavements with open-graded friction courses (OGFC). These pavements are common on motorways and high-speed roads, where the pavement thickness ensures long-lasting bearing capacity in the presence of heavy traffic and the interconnected air voids of the OGFC allow the water drainage from the pavement surface. In these cases, because of the pavement stiffness and the reduced mechanical properties of the wearing course, TDC generally precedes bottom-up cracking [1, 4].
In the initial stage, top-down cracks are isolated and can reach a length of several hundred meters. As the distress evolves, parallel longitudinal cracks are formed (“sister cracks”), fol-

lowed by short transverse cracks, ultimately leading to an alligator cracking pattern in the wheelpath. At the same time, the distress evolves in depth affecting increasing portions of the asphalt layer thickness and, in the advanced stages, can even lead to a generalized failure in the upper part of the asphalt layers, causing rainwater seepage and thus compromising the structural properties of the pavement [1].
These detrimental consequences can be avoided through a timely identification of TDC and immediate surface repairs. In fact, in this way, the pavement integrity can be preserved by simply replacing few centimetres of asphalt concrete, hence minimizing also the maintenance costs [1].
In recent years, machine learning (ML) methods have been often proposed for the automatic detection of pavement distresses [5-8]. Nevertheless, so far no scientific study has focused expressly on the identification of TDC with ML algorithms. In addition, the TDC issue is still little known to road agencies and practitioners, even though a survey of the Italian motorway network carried out in a previous phase of this project highlighted that, in some cases, TDC can affect up to 30 % of the slow lane length [4].
Within this framework, this paper describes a first attempt to develop an automatic method for the recognition of TDC on the pavement, based on ML algorithms. If implemented in a pavement management system (PMS), this tool can allow to plan timely surface repairs/ maintenance against TDC.

2 Development of the ML algorithm

2.1 Collection and pre-processing of the images

To develop the ML algorithm, the Automatic Road Analyzer (ARAN) images were used, which is an equipment mainly employed for roughness survey every six months on the entire Italian motorway network and, among other data, takes photographs of the pavement on the slow lane every 5 m with a georeferenced camera. Since the network is about 6000 km long (considering both directions), about 10^6 pavement images are available for every semester starting from the year 2008, when the equipment was first used. Therefore, the ARAN images, whose resolution is 1920x1080 pixels, potentially represent a large database for the development of the algorithm.
Nevertheless, not all images show longitudinal cracks and only a small part of these cracks is certainly attributable to TDC, whose unequivocal identification always requires to be supported by the analysis of field cores. Consequently, the algorithm was trained based on a limited number of images of pavements affected by TDC, which belonged to a portion of the Italian motorway network of 400 km surveyed in a previous phase of the project [4, 9]. Some images of recently paved areas were also considered to train the algorithm to the case of intact (non-cracked) pavement.
In addition, the ARAN images are characterized by a typical driver view (i.e. perspective, see Figure 1a), as the camera is mounted on the vehicle. Therefore, a pre-processing was necessary to straighten the images as well as to analyse the pavement continuously (the photographs are taken with a certain step).
Before any other pre-processing operation, the images (1800 in total) were anonymized for privacy reasons, covering the vehicle license plates with a dedicated open source software. Then, the images presenting longitudinal cracks (900) were labeled to train the algorithm. The label “TDC” was used in the presence of TDC, whereas the label “NO TDC” was used in the case of other longitudinal cracks that can be mistaken for TDC, such as longitudinal construction joints and cracks due to tire blowout of heavy vehicles [4]. Specifically, each crack was identified by its initial and final points. The rest of the images (900) referred to the case of intact pavement. Of these images, about 1400 were used for the algorithm training and validation, whereas about 400 were used for the algorithm test.

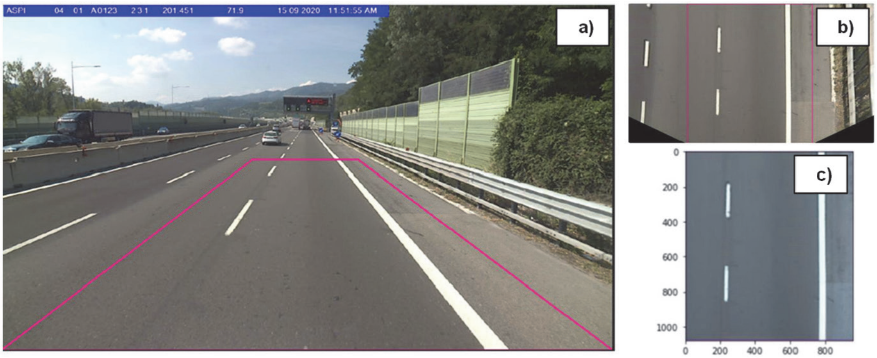

Figure 1 Pre-processing of the images: a) the original ARAN image with the area of interest; b) orthogonal projection of the area of interest; c) final image (dimensions in pixels)

After the labeling, the images were manipulated to obtain an orthogonal projection of the pavement surface. Part of the image was cut out and then the image was deformed on the basis of the horizontal markings (right margin and line of separation between the first and second lanes), as shown in Figure 1b. The manipulation was also applied to the labels, which were then transormed from pairs of points to rectangles. The new "horizon line" (the upper side of the trapezoid in Figure 1a), was placed at the farthest point where the image sharpness was deemed still acceptable. Even though the farthest area of the pavement was cut out, it was still possible to analyse the pavement continuously thanks to the availability of one photograph every 5 m, which ensured a certain overlapping between successive images. An example of a final image after the pre-processing procedure is shown in Figure 1c.

2.2 Image analysis criteria

The pre-processed images are analysed with the ML algorithm, which identifies the top-down cracks, assigning to each one a prediction confidence level between 0 and 1: the higher this value, the more confident the algorithm is of having identified a true top-down crack. Therefore, there can be several top-down cracks in a single image, some more likely than others according to the algorithm. As an example, Figure 2a shows two top-down cracks, one along the right wheelpath and one along the left wheelpath of the slow lane, with different prediction confidence levels.

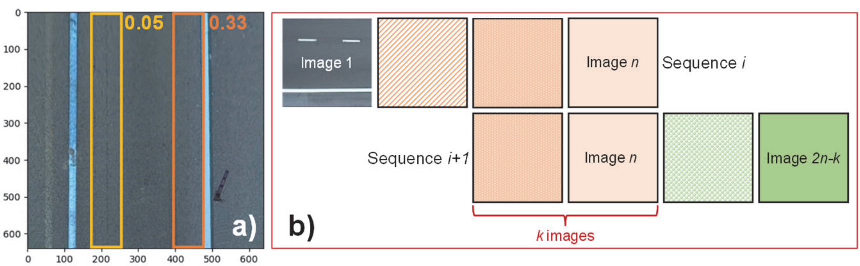

Figure 2 Image analysis: a) example of two potential top-down cracks with different prediction confidence levels; b) image sequences (scheme)

To improve the general performance of the algorithm, some image analysis criteria were defined. The first criterion involved the removal of redundant predicted labels within the single images. In fact, it was observed that in some cases the algorithm divided the same crack in multiple cracks with different confidence levels. If the horizontal distance between the cracks was less than a threshold value, the cracks were merged and a combined confidence level was considered. Such threshold (which is one of the free parameters of the ML algorithm) was chosen equal to 40 pixels in this study.
The other criteria were based on the peculiar geometric characteristics of TDC. As already mentioned in Section 1, TDC affects the wheelpath area, which is located at a certain distance from the horizontal markings delimiting the lane. Therefore, to eliminate false top-down cracks such as longitudinal construction joints [4], all the cracks falling within a certain distance from the markings were discarded. Such distance (which is another free parameter of the algorithm) was fixed equal to 40 pixels in this study.
Moreover, as anticipated in Section 1, top-down cracks have typical lengths of several hundred meters. Therefore, it was assumed that a true TDC would be continuous on several consecutive images. Consequently, sequences of images were considered, as schematized in Figure 2b. Each sequence included n images, and an overlap of k images was ensured between consecutive sequences. n and k are other two free parameters of the algorithm and were set respectively equal to 10 and 4 in this study. Analogously to what was done within the single image, the cracks present in different images of the sequence were merged if closer than 40 pixels horizontally. It is worth noting that, to associate the presence of TDC to the sequence, the presence of one single top-down crack is sufficient. This criterion allows to include the cases in which a very long top-down crack has been partially hidden by local surface repairs. In these cases, TDC is not evident on the pavement surface in a continuous way but could still be present below shallow surface repairs.

3 Results

3.1 Performance of the algorithm

Table 1 reports the performance of the algorithm for 20 independent motorway stretches. The algorithm performance was assessed through different metrics. Specifically, for the labeled images referring to the case of cracked pavement, precision and recall were considered:

$$\text{Precison} = TP/(TP + FP) \tag{1}$$

$$\text{Recall} = TP/(TP + FN) \tag{2}$$

where TP is the number of true positives, FP is the number of false positives and FN is the number of false negatives. Precision quantifies the percentage of correctly identified top-down cracks over the total of identified top-down cracks, whereas recall is a measure of the correctly identified top-down cracks over the total of existing top-down cracks. In this work, maximization of recall was preferred over precision, as – in the context of the larger purpose of this project – it is better to warn for a crack that is not TDC rather than skip a crack that is actually TDC. For this reason, another metric was also introduced, which is equal to 1 either if TDC is present in the image sequence and the algorithm finds it or if TDC is absent and the algorithm does not predict any top-down crack, 0 in the other cases. This metric, defined as "Boolean_kpi", is useful especially in the case of intact pavement, for which precision and recall are 0 (TP=0), and should be maximized as well. It is worth noting that Table 1 reports the average values obtained considering all image sequences within the single stretch. This is why some Boolean_kpi values are between 0 and 1.

Table 1 shows that, for cracked pavements, the recall and Boolean_kpi are close to 1 (except for stretch 7), whereas the precision is lower. At the same time, the Boolean_kpi is high also in the case of intact pavement (except for stretch 11). These results indicate that the algorithm overestimates the presence of TDC, associating it also to longitudinal cracks of different nature.
The algorithm performance can certainly be improved (some considerations are provided in Section 4), but can be considered acceptable at the stretch level. In order to validate the algorithm results at a narrower observation scale (e.g. at the sequence or image level), field cores were examined, as discussed in Section 3.2.

Table 1 Performance of the algorithm for different motorway stretches

Cracked pavement				Intact pavement	
Stretch	**Precision**	**Recall**	**Boolean_kpi**	**Stretch**	**Boolean_kpi**
1	1	1	1	10	1
2	0.46	0.97	1	11	0.25
3	1	0.98	1	12	1
4	0.50	1	1	13	1
5	0.94	1	1	14	1
6	0.71	1	1	15	1
7	0.38	0.13	0.75	16	1
8	1	1	1	17	0.72
9	1	1	1	18	1
				19	1
				20	1
Average	0.78	0.90	0.97	Average	0.91

3.2 Validation of the algorithm through field cores

A preliminary validation of the algorithm was done by considering a further 100 km trial section belonging to the Italian motorway network. All images obtained during the last ARAN survey (dated July 2021) were analysed with the ML algorithm and then a sample check of the algorithm output was carried out through a coring campaign. In this regard, 3 worksites were installed on the trial section to extract a total of 19 cores (14 on the longitudinal cracks and 5 control cores in the middle of the lane). It is worth noting that the coring operations required the carriageway narrowing (i.e. reduction of the number of lanes available for traffic). Therefore, to minimize traffic inconvenience, all coring operations were carried out at night.
The outcomes of the coring campaign are summarised in Table 2. In the table, the confidence classes A, B, C and D indicate respectively confidence intervals of 00.2, 0.20.4, 0.40.6 and ›0.6. The algorithm identified 4 different cracks: cores 1-5, cores 6-9, cores 10-11 and cores 12-14. However, 8 distinct cracks emerged from the analysis of the cores: TDC for cores 1-4 (longer than 450 m), 5 separate cracks due to tire blowout (cores 5, 6, 8, 10-11 and 12-14) and 2 reflective cracks (cores 7 and 9). Tire blowout cracks were simple incisions on the pavement surface [4], whereas reflective cracks affected almost the entire asphalt layer thickness. In general, no strong correlation was observed between the crack type and the confidence class, meaning that the algorithm was not fully able to distinguish different types of longitudinal cracks. Nevertheless, the lowest confidence (class A) was never associated to TDC, whereas it was associated to other longitudinal cracks in 4 cases out of 10, which represents a promising result.

Finally, it should be noted that the crack depth was between 60 and 105 mm in the cores affected by TDC (Figure 3). The mechanical model developed in a previous phase of the project [9] correctly predicted a maximum TDC depth of 109 mm for this pavement.

Table 2 Outcomes of the coring campaign

Worksite	km	Confidence class	Core	Distress
1	231+438	C	1	TDC
	231+581	B	2	TDC
	231+800	B	3	TDC
	231+910	B	4	TDC
	232+014	A	5	Tire blowout crack
	232+688	A	6	Tire blowout crack
	233+012	D	7	Reflective crack
	233+158	C	8	Tire blowout crack
	233+370	B	9	Reflective crack
2	265+582	B	10	Tire blowout crack
	265+781	A	11	Tire blowout crack
3	273+803	A	12	Tire blowout crack
	274+042	B	13	Tire blowout crack
	274+391	C	14	Tire blowout crack

Figure 3 Top-down crack observed during the coring campaign

4 Conclusions

This paper described a first attempt to develop an automatic method for the recognition of TDC on asphalt pavements, based on ML algorithms. The results obtained highlighted that currently the algorithm is able to identify longitudinal cracks, without however fully distinguishing their type (TDC vs. others). The possible causes include the limited number of images of top-down cracks used to train the algorithm, the low quality of the ARAN images available (which do not allow to recognize the peculiar features of TDC as compared to other longitudinal cracks) and the choice of the algorithm free parameters. In addition, more images and a greater variety (e.g. in terms of meteorological and light conditions, position of TDC) would probably be necessary for the algorithm training. In order to improve the algorithm, future work will involve the variation of the algorithm free parameters as well as the use of more images and with better quality. As for the latter aspect, the use of more advanced equipment in the future is already planned, and the algorithm was developed so that it can be easily adapted to different image acquisition systems.
Anyhow, this tool can be considered complementary to the mechanical model developed in a previous phase of the project to predict TDC depth. In fact, the prediction model provides a maximum TDC depth that can potentially occur in a given pavement, whereas the ML algorithm currently gives information on the presence/absence of longitudinal cracks. In the short term, the synergy between these two tools can be useful to identify the pavements more likely affected by TDC and organize an extensive coring campaign, with the final aim of improving both the ML algorithm and the mechanical model. In the long term, such tools can be used in a PMS to counteract TDC distress.

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