Automatic Road Crack Detection by Selection of Minimal Paths

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Résumé – Le relevé automatique des dégradations de surface à partir d'images de la chaussée est devenu un enjeu important dans de nombreux pays. Parmi les différentes méthodes proposées dans la littérature, cet article propose d'exploiter les chemins minimaux estimés dans l'image pour détecter les fissures. La méthode proposée prend simultanément en compte les caractéristiques photométriques et géométriques des fissures et requiert un minimum d'information *a priori*. Nous présentons les résultats sur des images collectées de manière dynamique (caméra embarquée).

Abstract – Automatic detection of road cracks from pavement images has become an important challenge in many countries. Among the different methods proposed in the literature, this paper proposes to combine shortest-paths previously estimated in the image. The proposed method takes account of both photometric and geometric characteristics of cracks simultaneously and requires a few informations *a priori*. It has been tested on image data sets collected by a dynamic imaging system.

1 Introduction

Monitoring the road conditions is an important task in many countries. The purpose is to determine the surface distress such as cracking and ravelling, which may require road maintenance and repair. Visual inspection has been the usual road survey method for many years. This task started thirty years ago to be performed from imaging systems which collect images of the pavement surface at traffic speed. Then, many efforts have been spent to use image processing techniques for the automatic detection of cracks. Pavement images are strongly textured and many cracks only appear as thin dark curves buried into textural noise. As a consequence, simple processing techniques produce many false positives, the detections are incomplete and the performance is dependent on the road texture.

According to [1, 2], the first image processing methods were based on the photometric characteristics of images. However, the histogram of road surface images usually depicts only one mode distribution, which makes the selection of an efficient threshold difficult. A wavelet transform-based approach has been explored in [3] but the main difficulty is to select the right scale for identifying cracks. The morphology methods take advantage of both photometric and geometric characteristics of cracks but the performances are strongly dependent on the parameter choices [4]. The supervised learning approaches can alleviate this default but they are time consuming and they require manual detection made by experts [5]. Recent and promising techniques rely on minimal path principles. Nguyen [7] introduces the estimation of constrained minimal paths in order to assign each pixel a probability to belong to a crack. The estimation of the minimal path is constrained by a direction and this approach detects only simple paths that are not representative of all possible and realistic cracks. In [6], the minimal paths are estimated between points of interest with a fast marching algorithm but the automatic selection of these end points is a difficult task.

As a result of the latter brief literature review, we decided to work with minimal paths since it allows to take into consideration the photometric and geometric characteristics of cracks and to be more robust to the image texture. Many algorithms exist to estimate minimal paths. The most famous and efficient ones are the Dijkstra algorithm [9] and the fast marching approach [10]. As shown on Fig.1, both algorithms detect the crack skeleton. However, Dijkstra performs better to closely follow the chaotic meanders of the crack path for such an image. This performance is due to the cost function that only depends on grey levels and in the proposed approach we chose the same cost. For the optimization which is out of the scope of this paper, we can use any of this two techniques but, at this stage, in our experimentations we have chosen the simplest algorithm to implement: the Dijkstra algorithm.

The scope of the paper is then to propose a new algorithmic scheme to select local minimal paths on sub-images and to merge the results together that allow the crack skeleton on the whole image to be detected. Section 2 describes the proposed method and first results are presented in section 3.

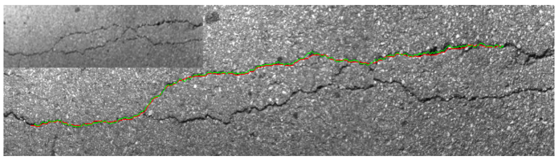

FIG. 1: Results obtained with Fast Marching (red) [6] and with Dijkstra algorithm (green) between points of interest.

2 Proposed approach based on minimal path selection

Assuming the features to detect in the images show darker pixels than the image background, the principle of this approach is to suppose that minimal paths in the image correspond to road cracks. In consequence, we want to estimate the minimal paths in each pixel of the image in order to select the ones which record the smallest path cost and that really belong to the cracks.

For Dijkstra algorithm, the conventional path cost function $C(s)$ is defined as the sum of grey levels along the feature, as follows:

$$C(s,d) = \sum_{m=s}^{d} I(m), \qquad (1)$$

with s the source, d the destination and $I(m)$ the grey level of pixel m. This criterion does not involve any geometry constraint or distance constraint and does not depend on the image quality. As a counterpart, applying Dijkstra algorithm between every pixel pairs would represent a huge computational task. An adaptation of Dijkstra algorithm to pavement crack detection has been proposed in [7] for which some directional and length constraints strongly reduces the computational burden. On the other side, the latter constraints limit the detection of different forms of cracks, especially the interconnected cracks. The second default is the way these minimal paths are exploited. The authors evaluate the probabilities of each pixel to be inside a crack based on $C(s)$. Then, all the pixels that are over a threshold are kept and the connection properties given by the minimal path are lost.

We propose an approach based on the selection of minimal paths with two major differences compared to [7]: (1) we propose to reduce the computation time by selecting significant sources and destinations for searching the minimal paths. (2) A different strategy is introduced to select the best minimal paths. The cost function is defined by equation (1) and the algorithm consists of the following four steps (see figure 2):

1. **Selection of the best endpoints:** In order to strongly reduce the calculation time, we consider pixel that are local minima, and we only retain those whose intensity is lower than a threshold S_a as a function of image histogram. Compared with the pseudo-ground truth, only a few selected pixels are inside the crack indeed, others represent potential sources of false alarms to be filtered out by the two next steps of the algorithm.
2. **Minimal path estimation between endpoints:** The Dijkstra algorithm is used, resulting in a collection of paths that are characterized by their length in pixels and their cost path value.
3. **Selection of minimal paths:** The statistics of the cost function affords roughly bimodal distribution for which a threshold S_c is easy to define. The selected paths may then represent two situations: the initiation and the endpoints are located inside the crack or only one among the two points are inside a crack. In the latter situation, the minimal path algorithm is able to attract a part of the path inside the crack while the other part is outside. This behaviour is the reason why a few spikes appear along the crack skeleton to be filtered out at the next step.
4. **Elimination of false alarm (spikes):** A spike is the path between extremities (e_i red point) and source of ramification point (s_i green point), cf. figure 3, step(4). The costs of these spikes are greater than the threshold S_c, same threshold as step (3). As result we remove these spikes and we detect the skeleton of the cracks.

The algorithm requires two parameters which are adjusted on statistics of each image. S_a and S_c that are the mean minus the standard deviation of respectively the grey levels of the image and the cost path values of the estimated minimal paths.

3 First Results

The algorithm has been tested on a few images (ten) which have been recorded by the French imaging system at traffic speed. Different kinds of cracks are considered with various forms and background lightings, figures 4 and 5. The image distribution is dominated by the image texture; the crack population is weakly represented (less than 2 % in pixels); some saturated pixels may appear in the images which have a larger mean value. These pixels are withdrawn from the basic statistic calculations and their influence is eliminated by the first step of the algorithm.

Algorithm based on selection of minimal paths

For each sub-image do

1. (a) Select lowest grey level pixels m_i in $P \times P$ sub-images
   (b) Select between m_i best endpoints a_i:
   (i) Estimate threshold S_a
   (ii) Select endpoints a_i with $I(m_i) \leq S_a$
2. For each a_i do
   Calculate shortest path costs $c(a_i, a_j)$ with $j = 1, .., 8$ corresponding to 8 possible endpoints neighbours in $Q \times Q$ sub-image
3. Select shortest paths based on $c(a_i, a_j)$
   (a) Estimate threshold S_c
   (b) Select best shortest paths with $c(a_i, a_j) \leq S_c$
4. Detection and suppression of spikes
   (a) Find extremity points : e_i
   (b) Find source of spikes points : s_i
   (c) For each (e_i, s_i) that are linked do
   Calculate cost $c(e_i, s_i)$
   (d) discard spikes with $c(e_i, s_i) \geq S_c$

FIG. 2: Method based on shortest path selection to detect the skeleton of cracks.

The assessment of the method is based on the comparaison between the pseudo-ground truth (which has been manually determined) and the crack skeleton. For convenience, two pixels of differences are allowed between the latter ground truth and the estimated crack as proposed in [1] (it is equivalent as applying a morphological dilation). Our results are compared to those obtained by [7] which provides a thick trace on each image with a much larger amount of pixels than expected, see figures 4.d and 5.d. As a consequence, a high rate of false alarm is reached and it does not give any chance to detect the width of the crack. The darkness of the image and the crack ramifications also disturb the performance of the method, see figure 4.3.d. In contrast, the proposed method is able to provide only the crack skeleton as shown on figures 4.b.

For quantitative evaluation, the rates of true positives (good detection), TP, false positives (false alarm), FP, and false negatives (undetected), FN, have been used to assess the performance of the algorithm. A good segmentation maximizes the first rate and minimizes the two others in order to afford a good positive predictive value, PPV:

$$PPV = \frac{TP}{TP + FP}$$

As a result, the proposed method reaches a larger mean PPV 80.35% than for Nguyen's method 64.76%, cf. table 1. However, the percentage of undetected pixels is not good (greater than 50%) for these three difficult images: 4, 5 and 10, cf. Fig.5. In 5 and 10, the obtained results is still more reliable than the results of [7] because of a high PPV. Unfortunately, results in 5 show the limits of the approach, this is an image where Nguyen outperforms the proposed approach. In conclusion, in most images, as opposed to [7], the proposed method can detect small cracks with 1 pixel width, figure 4.b, and leave the possibility open to detect the width of cracks in future works.

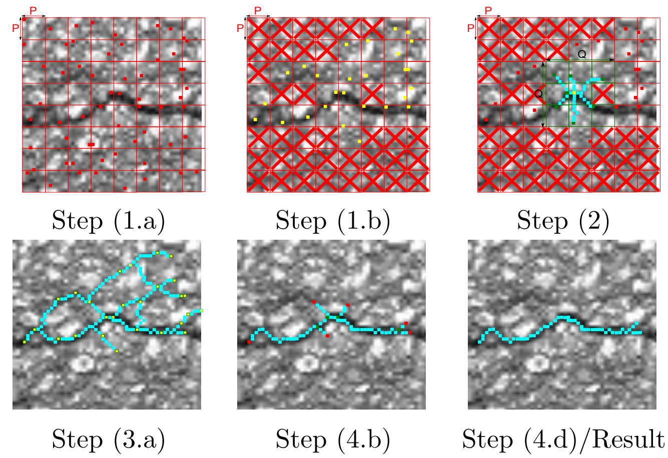

FIG. 3: Illustration of the four steps of the proposed approach – Step (1.a) shows the 8×8 sub-images and the selected pixels with the lowest grey-level (in red). Step (1.b) shows the selected best endpoints. Step (2) is the calculation of the 8 paths within the central sub-image. Step (3.a) shows the selected minimal paths whereas Step (4.b) gives the selected best shortest paths. Step (4.d) depicts the final crack skeleton with spikes discarded.

	Proposed approach		Nguyen approach	
image	PPV	FN	PPV	FN
1	**100,0**	23.35	65.89	**1.09**
2	**70.12**	15.22	67.83	**10.74**
3	**95.48**	**26.48**	83.39	35.93
4	18.32	**53.40**	**96.87**	75.00
5	**95.74**	53.55	71.17	**24.83**
6	**86.98**	16.96	54.00	**1.76**
7	**84.74**	28.67	46.95	**0**
8	**97.36**	12.59	53.97	**0**
9	**69.17**	28.57	46.14	**0.40**
10	**85.62**	56.25	61.40	**2.73**
Moy	**80.35**	31.51	64.76	**15.25**

TAB. 1: Results – Percentages of positive predictive values (PPV) and false negative (FN).

4 Conclusion and perspectives

In this paper, we have introduced a new method for automatic crack detection on road pavement images based on the automatic selection of minimal paths. Without any prior information neither directional nor distance con-

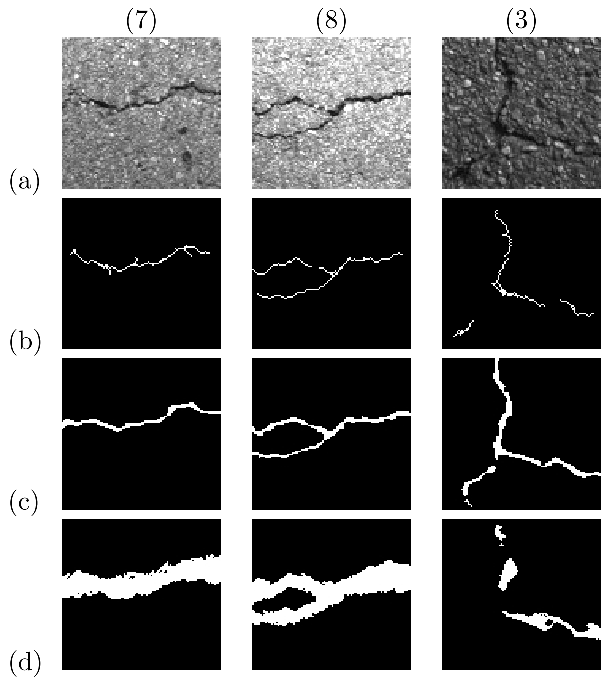

Fig. 4: Segmentation results – (a) original images, (b) Proposed approach, (c) Pseudo-ground truth images, (d) [7]. In (7), normal lighting with transversal crack, (8) brighter lighting with interconnected cracks and (3) very dark lighting with interconnected cracks.

straint the proposed algorithm detects the skeleton of cracks, it also achieves low score of false alarm. In the near future, step 4 of the algorithm will be completed to estimate the width of cracks and the algorithm will be tested on a bigger data set. It can also be generalized for thin objects or cracks detection in textured images from other domain of image processing (satellite or medical imagery).

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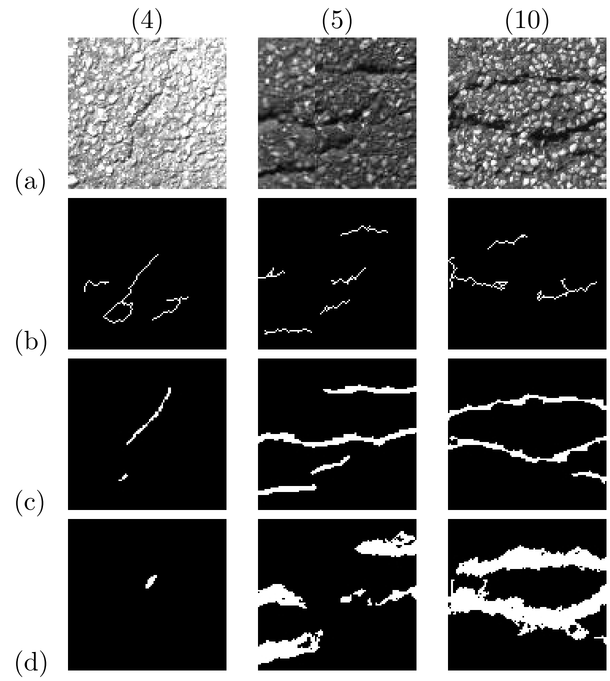

Fig. 5: Segmentation results with complex images – (a) original images, (b) Proposed approach, (c) Pseudo-ground truth images, (d) [7].

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