A COMBINED WAVELET-BASED IMAGE PROCESSING METHOD FOR EMERGENT CRACK DETECTION ON PAVEMENT SURFACE IMAGES

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ABSTRACT

This paper deals with a new approach for crack detection on road surface images using the wavelet transform combined with grey level morphology and segmentation. The pavement analysis context is briefly presented. Two image processing methods have been developed. Results obtained with “laboratory images” and “road images” are presented and discussed.

Keywords: wavelet, pavement cracks detection, edge detection, continuous transform,

1. INTRODUCTION

Pavement degradation is essentially due to heavy vehicle traffic and weather conditions. In France, pavement surveys represent several thousands of kilometres investigated each year. A major part of these surveys is made visually by qualified technicians driving along the road at a speed limit of around 5 or 10 kilometres per hour and using an on board dedicated data acquisition device. In these conditions, qualified staff and road users safety is not satisfying at all. The idea to improve this safety is ”to bring the road to the office”. For this, a vehicle moving with a satisfying speed to merge safely into the traffic would capture images of the road surface that could be then analysed. So the main objective of this research work is to automate progressively the work of the staff to detect and classify the pavement surface distresses using on road surface images.

The present paper only deals with a part of these applied research works concerning pavement crack detection.

Previous research works ([1], [2]) with segmentation image processing techniques led to not fully satisfying results for crack detection, due to the non homogeneity of pavement surface texture. Same conclusions have been recently exposed [3] by the PIARC (World Road Association) technical committee on surface characteristics.

The wavelet transform is used in many applications in signal and image processing as in data compression and signal denoising, but also edge detection and texture characterization [4]. This is this last use that suggests us to investigate such research line knowing that surface pavement distress is a texture break.

To our knowledge, few studies are available [5] in the literature on crack detection wavelet-based image processing methods.

In section 2, the problem position and used images are presented. Section 3 presents our image processing method combining wavelet with grey morphology and segmentation. Results are presented and discussed in section 4. Conclusion and perspectives are proposed in section 5.

2. THE CRACK DETECTION PROBLEM

2.1 Problem position

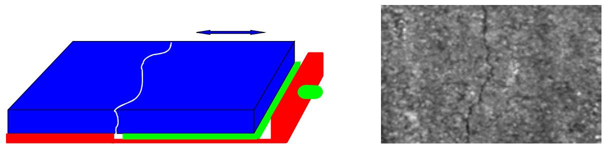
Pavement crack detection is not a “simple” edge detection problem due to the various pavement textures that can be encountered on “road image”. A way to reduce the texture effect is to use low spatial resolution images. But low resolution tends to erase thin crack signatures. So, they won’t be detected by image segmentation. Consequently, we have chosen to work with images whose spatial resolution is between 1 and 2 mm per pixel. If we look forward to the final on road operational system, such spatial resolution seems to be realistic, due to available technologies on the market.

2.2 Images used for the tests

The images we use are grey scale images. A crack corresponds to a connected set of pixels darker than pixels belonging to the rest of the texture. The shape of the crack is alike a group of linear structures.

In order to increase the problem understanding and to facilitate this new method development, we decided to use two types of pavement images.

The first type is called “laboratory images”. They are obtained by taking several images of a pavement sample whose crack width is controlled with an experimental apparatus shown in figure 1 (a). The spatial resolution of the image is about 1.05 X 1.25 mm per pixel. The picture (b) on figure 1 presents an example of a pavement surface image with a longitudinal crack of 3 mm width.



(a) (b)

Figure 1 : laboratory image with a 3mm width crack

The second type is called “road images”. They are images of different defects on various pavement surface of used roads. Here, the acquisition mode of the images is static, with no lighting control. In figure 2, we can see some shadows on the image due to the non control of the illumination. The spatial resolution of the image is round 1.5 X 2 mm per pixel.

Figure 2: static “road image”

Figure 3 shows profiles on the same line of three “laboratory images” (like image (b) of figure 1) that contains a crack whose average width is 1 mm for the first, 2 mm for the second and 3 mm for the third. In the graph we zoomed around the crack location and only plot from column 160 to 190. We note that it is very difficult to distinguish a 1 mm width crack from the texture. For such pavement (BB 0/10), a crack width of 3 mm can be visually discriminated from the pavement surface texture. As we can see in figure 3, the crack represents a singularity in the signal image, that is the reasons for proposing a wavelet-based image processing method.

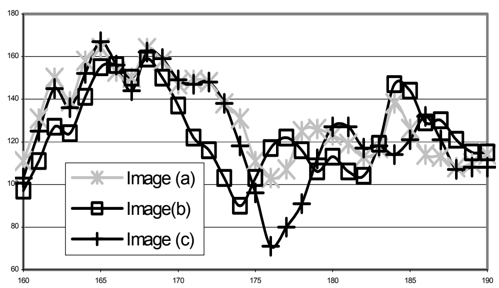


Figure 3: crack profile

3. CRACK DETECTION METHOD PROPOSED

3.1 Pre-processing

The pre-processing is used to reduce the importance of the texture and then to have a better detection of the crack.
For this, we use a two dimensional grey scale morphological filtering [6].

3.2 Wavelet processing

In this section, we remind some properties of the wavelet transform that are useful to design our wavelet-based image processing method.

3.2.1 Definition

A wavelet ψ is a zero mean function: $\int_{-\infty}^{+\infty} \psi(t)dt = 0$, that is normalized to $\|\psi\| = 1$ and centered around $t = 0$. We can dilated ψ by a scale factor s, and translated it by u to generate a set of vectors:

$$\Psi_{u,s} = \frac{1}{\sqrt{s}} \Psi(\frac{t-u}{s}), s \in \Re^{+}, u \in \Re, \qquad (1)$$

ψ is also called “the mother wavelet”.

Let f be a square integrable function. The continuous wavelet transform $Wf(u,s)$ of a function f is defined by:

$$Wf(u,s) = \left\langle f, \Psi_{u,s} \right\rangle = \int_{-\infty}^{+\infty} f(t) \cdot \frac{1}{\sqrt{s}} \Psi^{*}(\frac{t-u}{s})dt, \qquad (2)$$

$Wf(u,s)$ is also called the wavelet coefficient.

3.2.2 Singularity detection

A remarkable property of the wavelet transform is its ability to locate a singularity in a signal.
Figure 4 presents a signal and its wavelet transform computed with the derivatives of a Gaussian [4].
Finer scales are at the top. Zero values are represented in a medium grey level. So, regular part of the signal is also represented by a medium grey level.

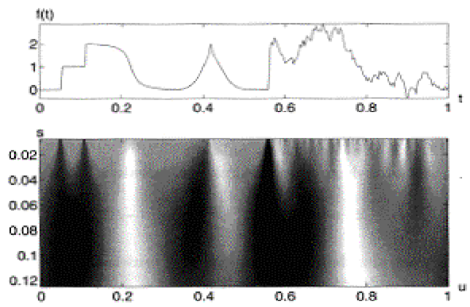


Figure 4: a signal and its wavelet transform

In figure 4, we can see the presence of maxima at finer scale where a singularity occurs. Yet, we can also remark that if we move too far in the scales, then wavelet coefficients merge and we cannot distinguish a maximum from another one. It is principally this property of detecting singularities we propose to use.

Here, we consider the image line by line, that is to say that we use lines as a succession of 1D signal. Then, we compute the wavelet coefficient by using the 1D continuous wavelet transform on each line. This is made for several scales. Two methods have been tested.
In the first one, we compute the 1D continuous wavelet transform for a given scale. Then, a post-processing is performed.
In the second method, we compute the 1D continuous wavelet transform on each line of the image and for several scales. Thus, we get as many wavelet coefficient images as the number of scales computed. Then, we merge these images in order to detect cracks. Here, we add all these absolute wavelet coefficient images. Then, a post-processing is performed.

3.3 Post-processing

The post-processing consists in searching for the wavelet coefficient maxima. For this, one divides the image into 10 pixel width bands. Then one searchs for the maximum in each band, line by line. Doing this, one only detects one maximum per band but one rarely meets two cracks that are separated of one or two centimeters except at the beginning of a ramified crack. Once a binary image has been built with the maxima localization, we eliminate the isolated pixels in order to clean the image using a "salt and pepper" morphologic filter. Finally we perform a binary morphological dilation with a 3X3 structuring element and keep only pixel sets whose size is above a given threshold.

4. RESULTS AND DISCUSSION

4.1 Choice of the wavelet function to use

Sets of wavelets have been tested on various synthetic images to choose which one gives the best results. Different targets have been used on these synthetic images to qualify the ability of the wavelet to detect cracks such as edges. The contrast between the target and the background has been also modulated. Finally, noisy synthetic images have been used to test the robustness of the previously selected wavelet.

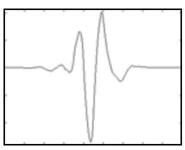


Figure 5 : mother wavelet "Symlet 5"

In this paper, results have been obtained with the wavelet symlet 5 displayed on figure 5.

4.2 Different steps of the processing

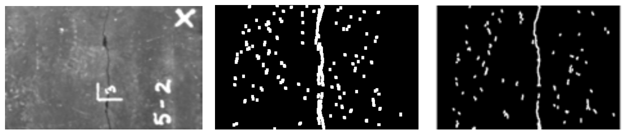
In this part, we present results for two types of pavement surface.

4.2.1 Results on "laboratory images"

Figure 6 and 7 display two "laboratory images" used to test methods proposed in part 3.3.

(a) (b) (c)

Figure 6: Rough texture laboratory pavement surface image and binary images after processing



(a) (b) (c)

Figure 7: Smooth texture laboratory pavement surface image and binary images after processing

Results obtained with the first method are displayed in figures 6 and 7 (b) and with the second in figures 6 and 7 (c). We can observe that the second method gives a cleaner image. Nonetheless, both one display a low sensitivity to the presence of painting signs on the pavement surface.

4.2.2 First method analysis

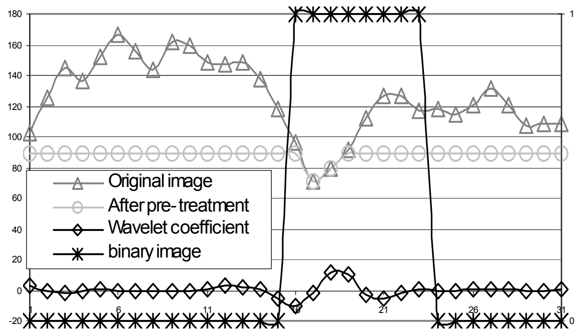


Figure 8: Crack profile extracted from image of figure 6 at different steps with the first method

Figure 9: Crack profile extracted from image of figure 7 at different steps with the first method

Figure 8 and 9 show profiles at different steps of the first crack detection method. We can observe that the pre-processing reduces the influence of the texture and tends to preserve a partial signature of the crack. The intensity distribution of the wavelet coefficient values around the crack still depends on the original roughness of the pavement surface. The post-processing partly corrects this behaviour.

4.2.3 Second method analysis

Figure 10 and 11 show profiles at different steps of the second crack detection method. The main difference relies in the increasing of the intensity distribution of the wavelet coefficient values around the crack due to the use of 8 scales. It leads to a better detection of the maxima linked to the crack presence. The dependency to the original pavement surface texture is reduced.

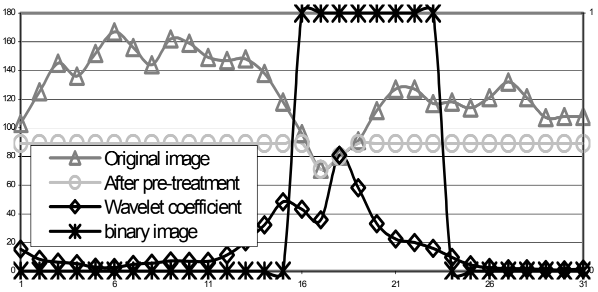


Figure 10: Crack profile extracted from image of figure 6 at different steps with the second method

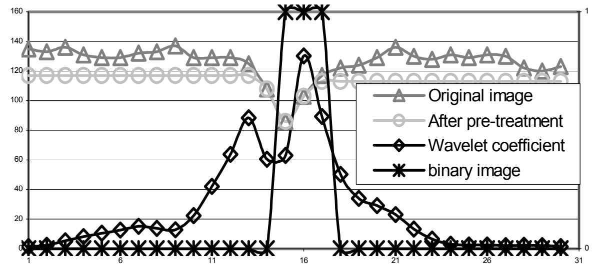


Figure 11: Crack profile extracted from image of figure 7 at different steps with the second method

4.3 Application to "road images"

Figure 12 shows the results obtained with a "road image", which contains a branching crack (image a). The first method has been applied to this image and the result is presented on image (b). We observe that the transversal part of the crack is not detected due to this 1D continuous wavelet use. This problem is easily solved by computing the wavelet transform along both lines and columns and merge the two coefficient maps computed. For the result (image c) showed in figure 12, we add the two-coefficient map before the post-processing step.

(a) (b) (c)

Figure 12: detection of a branching crack

This illustration with a "road image" shows the limitation of the 1D continuous wavelet approach despite of its strength in comparison with the results obtained.

5. CONCLUSION AND PERSPECTIVES

In this paper, we have presented two variations of a new image processing approach to detect emergent crack on pavement surface images. They use the merging of a 2 dimensional grey and binary morphology treatment with a 1 dimensional wavelet approach and are very promising. According to the results presented, we can say that the second method seems more efficient than the first one. Nonetheless, the wavelet coefficient maxima location on the map could be improved. The wavelet scales interval we used and the step between them have to be optimized.

Furthermore, we plan to work on real pavement texture for synthetic images to identify a quality factor and improve the choice of the best-adapted wavelet to our problem. The influence of the texture on to the image processing performance for crack detection has to be studied in depth. The use of the 2D continuous wavelet transform has to be examined and tested on pavement surface images.

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