CrackIT – AN IMAGE PROCESSING TOOLBOX FOR CRACK DETECTION AND CHARACTERIZATION

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ABSTRACT

This paper presents a comprehensive set of image processing algorithms for detection and characterization of road pavement surface crack distresses, which is being made available to the research community. The toolbox, in the Matlab environment, includes algorithms to pre-process images, to detect cracks and characterize them into types, based on image processing and pattern recognition techniques, as well as modules devoted to the performance evaluation of crack detection and characterization solutions. A sample database of 84 pavement surface images taken during a traditional road survey is provided with the toolbox, since no pavement image databases are publicly available for crack detection and characterization evaluation purposes. Results achieved applying the proposed toolbox to the sample database are discussed, illustrating the potential of the available algorithms.

***Index Terms*—** Toolbox, road survey, crack detection and characterization, image processing, pattern recognition

1. INTRODUCTION

The development of high-speed image acquisition systems to collect information about pavement surface condition, coupled with automatic image analysis for the detection and characterization of road surface distresses, allows for the pavement surface observation of extensive road networks, making it a more feasible task [1] [2]. Nevertheless, high-speed image acquisition systems produce very large amounts of data (images) that need to be efficient and accurately processed, to get a reliable assessment about the road condition [1] [3]. The implementation of automatic pavement surface image analysis systems poses some challenges, requiring complex data processing techniques to handle pavement condition and texture variability [4] [5].

This paper proposes a toolbox that includes a set of image processing algorithms, for the analysis of images taken during road surveys, to automatically detect and characterize road cracks, the most common type of pavement surface defects [6]. The paper is organized as follows. Section 2 briefly reviews the crack detection and characterization state-of-the-art, and how authors typically organize the employed algorithms. Section 3 describes the proposed image processing toolbox for automatic crack detection and characterization, denoted *CrackIT*. Section 4 presents sample experimental results obtained, while section 5 draws conclusions and presents hints for future work.

2. LITERATURE REVIEW

In the scientific literature, the number of recent published papers dealing with crack detection and crack type characterization shows an increasing interest in this area. Recently, some authors have proposed ways to organize/structure the existing crack detection and characterization algorithms.

A summary of available techniques is presented in [7], organized into four processing stages: (i) <u>pre-processing</u>, mainly based on contrast stretching and histogram equalization techniques, reducing the effects of shadows caused by trees, viaducts and other objects located at the road shoulder, equalizing variations in the pavement texture and mitigating the contrast between wet and dry areas of pavement surface; (ii) <u>road image segmentation</u>, based on fixed or fuzzy entropy thresholding operations, as well as thresholding on the spatial coefficients of Wavelet transform, to separate crack information from the rest of the image; (iii) <u>post-processing</u>, mainly based on morphological and connectivity searching operations, to reduce the number of false cracks previously detected, as well as linking crack regions to form groups of connected pixels of darker intensities than their surroundings; (iv) <u>crack extraction</u>, employing techniques such as the Hough transform or neural networks, among others, to identify cracks and locate them in images.

In [3], existing semi-automatic and automatic crack detection approaches are discussed, and organized into five stages: (i) <u>histogram analysis</u>, using thresholding techniques (either adaptive or local) following Gaussian hypotheses, to distinguish between crack pixels and the image background; (ii) <u>mathematical morphology tools</u>, usually adopted to alleviate the problem of false crack detections, enforcing the spatial continuity between groups of connected components detected as cracks; (iii) <u>a learning phase</u>, using for instance, a trained neural network, or other machine learning technique; (iv) <u>image filtering</u>, including edge detection, adaptive filtering, contourlets, methods based on Gabor filters, finite impulse response filtering or filtering techniques based on partial differential equations, among others, exploring the knowledge that cracks correspond to deviations from a regular image texture; (v) model-based approaches, usually exploring local, global or multi-scale properties of cracks in images, based on photometric, geometric or frequency properties.

Another proposal to structure crack detection and characterization algorithms is presented in [8], consisting of four main stages: (i) image pre-processing, usually applied to enhance the contrast between crack regions and the image background, to smooth images that exhibit an highly random texture, or to reduce noise that corrupts the image and hampers road distresses detection; (ii) feature extraction, computing the value of selected characteristics to be used by a pattern recognition system for crack identification, exploiting crack pixels' photometric, geometric or frequency properties; (iii) crack detection and classification, using techniques as thresholding, neural networks, k-NN, boosting or support vector machine classifiers; (iv) crack type characterization, using another pattern recognition system to classify cracks based on their shapes [9].

3. THE *CrackIT* TOOLBOX

This paper proposes a crack detection and characterization image processing toolbox, including a set of tools for the evaluation of the produced results. The *CrackIT* toolbox follows the generic system architecture of Figure 1, being structured into four main modules: (i) image pre-processing, including algorithms for image smoothing, white lane markings detection, pixel intensity normalization and saturation; (ii) crack detection, based on pattern classification techniques; (iii) crack characterization into types, notably classifying detected cracks as longitudinal, transversal or miscellaneous, and including a severity level assignment; (iv) evaluation routines, to compute ROC curves, and standard metrics such as recall (*re*), precision (*pr*) or F-measure (*Fm*).

3.1. Pre-processing

The pre-processing algorithms, which can follow block-based (*bb*) or pixel-based (*pb*) approaches, include: (i) image smoothing (*pb*), to reduce image background pixel intensity variance, without significantly affecting the intensity of pixels belonging to cracks; (ii) white lane lines detection (*bb*), identifying road areas painted in white; (iii) preliminary selection of crack blocks (*bb*), allowing a first detection of prominent cracks; (iv) image normalization (*bb*) and saturation (*pb*), to reduce the non-uniform image background illumination and remove groups of bright pixels corresponding to specular reflections, respectively.

The image smoothing techniques implemented include: (i) anisotropic diffusion, following Perona and Malik's algorithm [10]; (ii) morphological smoothing, with an opening-closing filter [11, pp. 369-373], or using an alternating sequential filtering, adopting iterative opening and closing operations with structuring element (*se*) of increasing size, envisaging smoother results [11, p. 371];

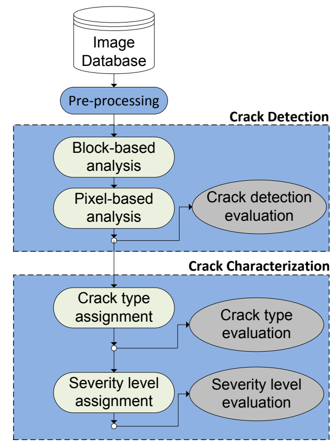

Figure 1: *CrackIT* toolbox architecture.

(iii) a combination of morphological erosion and dilation operators [12, pp. 102-103]; (iv) stationary wavelet transform with the Symlet decomposition filters [13, pp. 7-27 until 7-30]; (v) an unsupervised non-linear, non-parametric and adaptive filter method, based on a joint-entropy measure, denoted UINTA [14]; (vi) an unsupervised information-theoretic adaptive image filtering with reduced dimensionality, denoted R-UINTA [12, pp. 115-118]. Sample R-UINTA smoothing results are shown in Figure 2.

White lane lines (*wll*) are groups of connected image blocks of pixels with intensity higher than a certain threshold, empirically chosen by the system operator.

The preliminary selection of prominent crack blocks is based on two simple local statistics: average and standard deviation of gray level values inside non-overlapping image blocks. The system scans the images vertically and horizontally, searching for image blocks that present abrupt intensity variations in comparison to their neighbors. The prominent cracks (groups of connected crack blocks) allow for a supervised normalization of the intensities, which tends to equalize the average intensities for those image blocks preliminary classified as not containing cracks, the pre-selected crack blocks remaining unaffected. Afterwards, images can undergo a saturation procedure, where pixel intensities higher than the image average intensity are replaced by that mean value [4].

3.2. Crack Detection

Crack detection algorithms can follow a block-based (*bb*) or a pixel-based (*pb*) approach, as illustrated in Figure 3.

3.2.1 Block-based Crack Detection (bb)

For the block-based approach, the toolbox implements a pattern recognition system which labels non-overlapping image blocks either as 'crack' or 'non-crack'. A two-dimensional feature space is considered, using the two local statistics referred in section 3.1: block pixel intensity average and block intensity standard deviation. Different classification strategies are available, notably six supervised and six unsupervised [15] [16] [17], as illustrated in Figure 4.

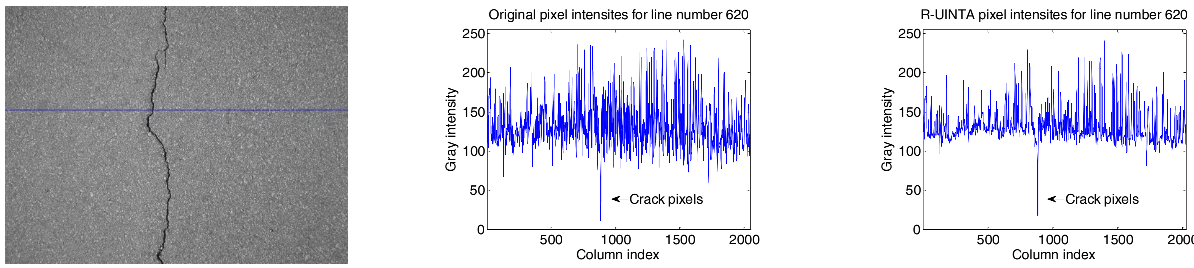

Figure 2: Sample image smoothing results using of R-UINTA strategy: original (middle) and smoothed (right) pixel intensities, with crack pixel intensities almost unaffected.

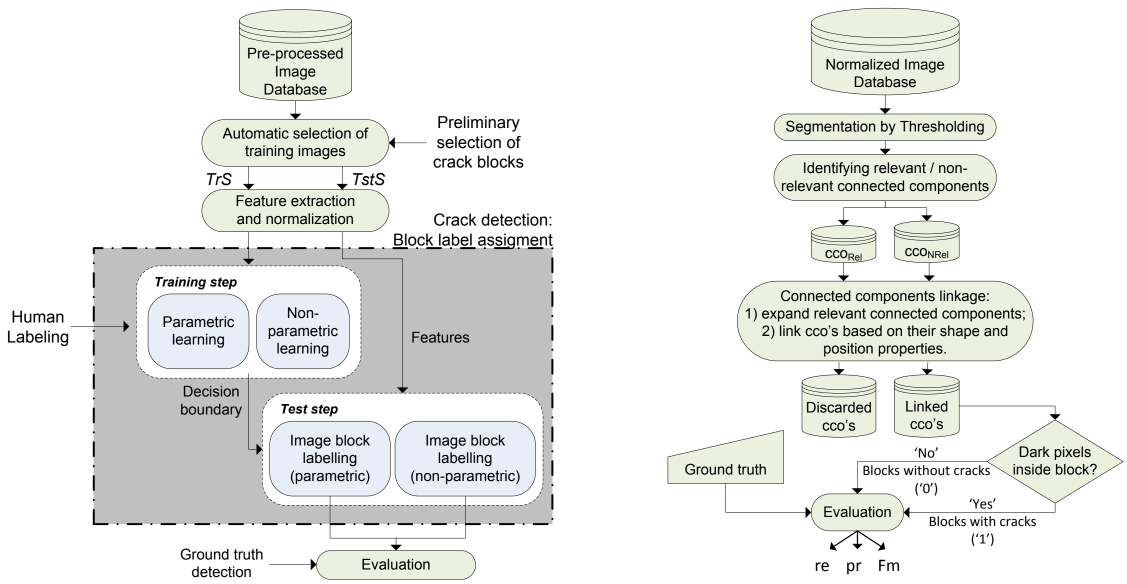

Figure 3: Architectures for automatic crack detection stage: block-based (left) and pixel-based (right).

A training from samples paradigm is adopted, using the results obtained during the preliminary selection of crack blocks, to split the image database into training (*TrS*, used for system's training and composed by the images with longer prominent cracks) and testing (*TstS*) sets.

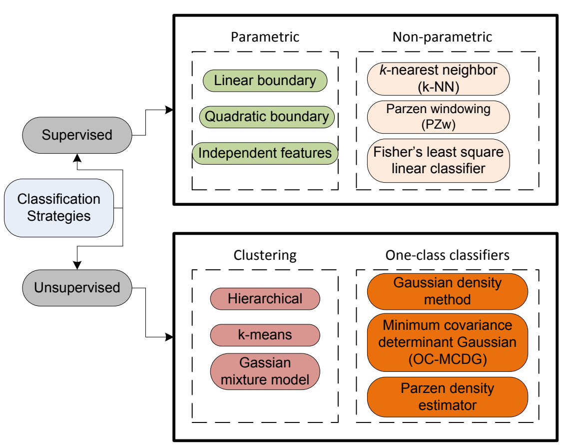

Figure 4: Diagram of the classification strategies considered.

In addition to feature extraction, a feature normalization algorithm is also available, helping to improve classification performance, by aligning the features computed in different images. Sample detection results are shown in Figure 5.

3.2.2 Pixel-based Crack Detection (pb)

For the pixel-based approach, pre-processed images are segmented, based on a dual intensity threshold automatically computed for each image, to distinguish between crack pixels and those belonging to the image background. Crack candidates are then found by grouping crack pixels using a connected components algorithm, thus identifying relevant cracks (cco_{Rel}), i.e., those that simultaneously fulfill a set of three geometric requirements adopted for this purpose, notably: (i) more than 70% of eccentricity for an ellipse fitted to it; (ii) ellipse major axis longer than 25 pixels; (iii) width higher than or equal to 2 mm (ratio between the number of pixels in the *cco* and its skeleton.

The remaining are non-relevant crack connected components candidates (cco_{NRel}). A linking algorithm is also available to decide whether pairs of crack candidates should be linked together. This uses a pattern recognition system exploiting two geometric features, based on the connected components shape and position in the image, to find groups of linked connected component objects (*cco*). Each set of linked *cco* identifies a global crack [4]. Sample pixel-based crack detection results are shown in Figure 5.

3.3. Crack Characterization

The characterization of detected cracks into types (longitudinal, transversal and miscellaneous, a subset of

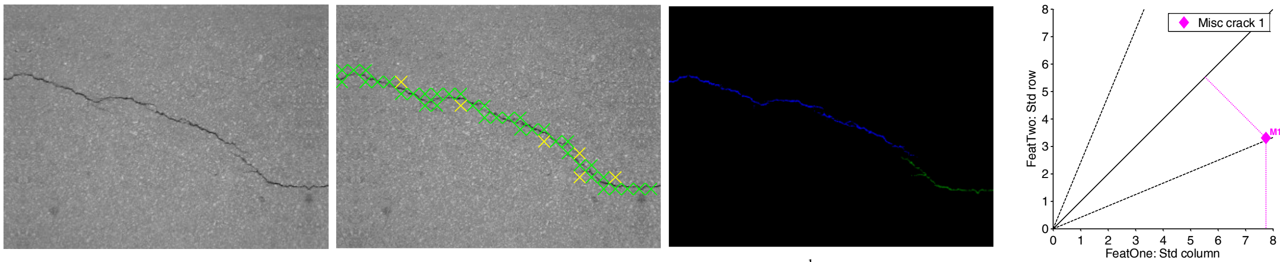

Figure 5: Sample results: original image (left); crack detected using *bb* approach (2nd), exhibiting true (green) and false (yellow) positives; global cracks identified using *pb* approach (3rd), each depicted in the same color; and the crack type assigned (right) based on the *std* of *cco*'s pixels coordinates (horizontal and vertical), showing decision boundaries (dashed lines) and feature space division (solid line).

those identified in the Portuguese road surface distress catalog [18], as well as other national distress catalogs, like the US [19], French [20] and Spanish [21] ones) follows the previous work published by the authors in [4]. Sample results are shown in the right plot of Figure 5.

The assignment of severity levels to the detected crack segments relies on the computed measurement of the crack's width, calculated as the ratio between the crack segment area and the number of crack pixels belonging to crack skeleton. Severity level 1 is assigned to cracks with no more than 2 mm width, while severity levels 2 or 3 are assigned to cracks of more than 2 mm width.

3.4. Evaluation

Several routines allows for the evaluation of the results obtained, allowing to assess the systems' performance at any stage of the processing, either preliminary labelling of crack blocks, crack detection (*bb* or *pb*), as well as crack characterization, are available. The *re*, *pr* and *Fm* metrics are used to infer about the suitability of the adopted classification strategies for the envisaged application. The computation of some of the desired metrics requires that "ground-truth" is supplied to the system.

4. EXPERIMENTAL RESULTS

The sample database that will be made available with the toolbox contains 84 gray-level pavement surface images (1536×2048 pixels), acquired by an optical device. Each square pixel occupies approximately 1 mm^2 of pavement surface. Also ground-truth crack detection and characterization results are provided for these images.

Part of the Matlab algorithmic implementation was supported on the PRTools [22] and DDTools [23] toolboxes. The *CrackIT* toolbox will be made freely available at http://www.img.lx.it.pt/CrackIT/.

For the sample images, the *CrackIT* toolbox algorithms achieve an *Fm* metric of about 97%, corresponding to $re = 98.4\%$ and $pr = 95.5\%$, when merging the adopted parzen windowing classification strategy results (*bb* and *pb*), using R-UINTA smoothing. *CrackIT* was able to automatically detect all cracks identified in the ground-truth, thus corresponding to 100% of recall when evaluating *pb* crack detection results. A qualitative evaluation of the severity level assignment was performed by a human expert, who infers the width of a crack by visual inspection of the corresponding images, and no inconsistencies were found in the automatically produced results.

These results are considered good, notably when taking into account the difficulty of the crack detection task even for a human observer. In fact, the typical variation of human labeling leads to a result imprecision of around 1% to 2.5%, due to the human ambiguity in recognizing patterns [24].

5. CONCLUSIONS AND FUTURE WORK

The proposed toolbox allows achieving good crack detection and characterization results, but dealing with very thin cracks (of less than 2 mm width) can be a difficult task, as many false positives may appear, notably due to the difficulty of distinguish cracking from raveling distresses. Still, *CrackIT* targets the detection of cracks with at least 2 mm width, thus in line with the guidelines given by experts on detecting very thin cracks using automatic crack detection systems, as mentioned in [25] [26]. Moreover, the algorithms available enable the detection of multiple cracks in the same image, taking about 4 min to process the 84 images using a Qosmio X500-11U laptop.

There are no available protocols or standardized methods for evaluating the performance of the developed systems and to compare the published approaches, leading the authors to consider different protocols, despite some existing harmonization efforts [3]. Thus, the availability of the *CrackIT* toolbox intents to contribute to the advancement of crack detection and characterization using road pavement surface digital images, by sharing a development and evaluation platform.

It is expected that this toolbox will be extended, for instance to include algorithms to further reduce pixel intensity variance in non-crack blocks, or increase robustness to image brightness variations. Also the usage of alternative/additional features to be used for crack detection, or enhanced crack linkage algorithms, are being investigated. External contributions by other researchers are welcomed – please contact the authors.

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