Automatic Classification for Pavement Cracks for Mobile Mapping Data

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Key words: Crack classification, Pavement, Digital image processing techniques.

SUMMARY

Over recent years, the cracks classification of the actual pavement sections has been one of the most motivating subjects in highway transportation applications and research. Cracks classification is indispensable for maintenance priorities. There is no standard method for classification that indicates the capability of crack classification under different conditions such as different pavement textures, different illumination and shades. Also there are no standard specifications that can be used everywhere. The standard specifications are different from one country to another and sometimes from one state to another in the same country. Every road authority has its own method for the classification. The authors derived that the differentiation between crack types is considered as a challenge more than detecting cracks itself. The presence of noise and extrinsic objects will reduce the accuracy of the crack classification rate. The precise classification results need robust pre-defined crack extraction steps. Digital image processing techniques are already widely adapted as tools for crack classification. Previously several image processing algorithms are usually suffering from various shortcomings on cracks classification sides. In this study a novel methodology for classifying crack types will be presented. This algorithm will detect crack types automatically. Finally, it can overcome some drawbacks and shortcomings for previous crack classification algorithms particularly in the case of complex block cracks such as noise problem, lane marking problem, and lighting problem.

100% (percentage of correctness classification rate) could be obtainable for one case study of continuous mobile mapping images collected by Lehmann + Partner GmbH company-Germany. The developed algorithm delivers an average computation time of 3.8 min to complete crack classification.

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1. INTRODUCTION

Cracking is defined as an individual (single) crack or a network of cracks (Block type) or a crack accumulation (FGSV 2006). Individual (single) cracks may be distributed in several directions as either vertical, horizontal, or transverse. In a network cracks are connected to one another, similar to a net, with the size being diverse. A network of cracks is classified as a block type. The individual cracks either vertical, or horizontal, or transverse are measured by its length, width, orientation and area of cracking region. While the crack accumulation or network of cracks (block type) are measured by area of the cracking region (AL-MISTAREHI 2015).

2. CRACKS CLASSIFICATION ALGORITHMS

GEORGOPOULOS ET AL. (2005) classified cracks based on the orientation directions. Moreover back propagation neural networks is addressed for crack classification (CHOU ET AL. 1994; LEE ET AL. 2003; HSU ET AL. 2001, CHOU & SALARI 2012). The projection histogram method is able to classify cracks by examination the peaks of projection vectors (CHENG & MYOJIM 1998; RABABAAH ET AL. 2009; TEOMETE ET AL. 2005). SALARI ET AL. (2010) proposed a 2D-feature mapping method for cracks classification either alligator cracking, block cracking, longitudinal cracks and transverse cracks.

JAVIDI ET AL. (2003) addressed Hough Transform method. Every classification method has its own problems and defects. Such as the state-of-the-art Hough Transform method (JAVIDI ET AL. 2003) suffers from two significant problems as follows: (i) it can be prone to failure to check pixel connectivity in the case of large number continuous pavement images; (ii) although edge pixels are connected, the count of the accumulator cell can not reflect the length of crack segment. Some other methods are based on predefined characteristics of each individual crack pattern (WANG & HARALICK 2002). It is called crack classification standard method (YING & SALARI 2009). YING & SALARI (2009) state that the crack classification standard method outperforms significantly the state-of-the-art methods such as the Hough Transform method. For example crack classification standard method classify cracks based on predefined orientation angle and crack branches number. Moreover it determines the crack length with taking pixels connectivities into consideration. While Hough Transform method can classify cracks but can not detect its length exactly.

Furthermore YING & SALARI (2009) illustrate that crack classification standard method is easier to relize than other complicated methods such as back propagation neural networks (CHOU ET AL. 1994). So it is just based on crack orientations and number of crack branches. Nevertheless, in the case of complex compound cracks pavement images and block cracks, the projection histogram method (TEOMETE ET AL. 2005) and other methods fail while crack classification standard method continues to work. So it is not very sensitive to noise and can deal with poor quality images.

As a logical follow-up, all the previous algorithms face some obstacles and problems. The present paper adapts and modifies a crack classification standard method (YING & SALARI 2009) to meet the requirements and demands. As a result the modified crack classification standard method realizes a raise in automation. It represents a direct solution for crack classification with different pavement texture. In the following a detailed description of the modified crack classification standard method is demonstrated in order to introduce the whole used steps.

3. PROPOSED ALGORITHM FOR CRACKS CLASSIFICATION FOR MOBILE MAPPING DATA

A direct crack extraction from continuous pavement images based on the combination between different image processing techniques and some modifications of previous algorithms was presented by AL-MISTARHI & SCHWIEGER (2015). The final hypothesis and the assumption is built by existing ellipse binary mask automatically around corrected cracks regions only. The present paper aims to improve the automation degree of AL-MISTARHI & SCHWIEGER (2015) by adding a crack classification part. This improvement will generate fully automated backage for crack detection and classification from continuous pavement images (mobile mapping data). This added improved part is developed by modifiying the crack classification standard method (YING & SALARI 2009). In the following a detailed description of the modified crack classification standard method is demonstrated in order to introduce the whole steps as shown in figure 1 below.

Based on YING & SALARI (2009), the orientation angle Ω is defined as an angle between the horizontal axis (driving direction) to the start and end points of each crack. YING & SALARI (2009) introduced limits of the orientation angle Ω with the horizontal axis, such as (30°, 60°). These numbers (angles limits) are supposed as a specification for the control crack classification of either horizontal, vertical, or transverse. Therefore, the crack classification standard method (YING & SALARI 2009) is modified to meet the objectives of this paper application as follows: (i) the orientation angle Ω is defined as an angle between the horizontal (+x-axis) and the major axis of the region (ellipse shape), either clockwise or counter-clockwise. This orientation angle Ω ranges from -90° to 90°. It is obtained automatically from applying the previous modified binary mask algorithm step (AL-MISTARHI & SCHWIEGER 2015); (ii) Based on the knowledge of the YING & SALARI (2009) algorithm, general specifications are generated to connect between the crack type and its orientation, automatically. In this paper, crack classification is done based on these general specifications. The classification of cracks is implemented as follows (YING & SALARI 2009):

1- The vertical individual cracks have an orientation angle ($\Omega >= 60^{o}$).
2- The horizontal individual cracks have an orientation angle ($\Omega <= 30^{o}$).
3- The transverse individual cracks have an orientation angle ($60^{o} > \Omega > 30^{o}$).

4- The network of cracks (block type) have different orientations associated to different branches. There is no specified range for its orientation.

Consequently, according to (YING & SALARI 2009), the type of crack is determined by its angle with the horizontal axis Ω and the number of branches in the crack. The algorithm for the determination of the number of branches is not explained in more detail by YING & SALARI (2009). Therefore, this study develops an algorithm for counting the number of block crack branches within an image as follows:

Preparing Stage: A statistical analysis is performed for most of the block crack images to determine the range of block crack branch area lengths and the range of block crack branch area widths. These numbers are considered to meet the requirements for generating the rectangle binary mask shape for (ii), the latter step. In this paper, the results of the statistical analysis over most of the block crack branches are as follows: (1) the range of block crack branch area lengths is between 0.3 to 0.6 m on the ground, which equals 250-500 pixels on the image. (2) The range of block crack branch area widths is between 0.07 to 0.1 m on the ground, which equals 58-83 pixels on the image. This stage is done just once using the images of one case study only. The results of the statistical analysis are used as a pre-defined conditional statement values in all case studies of this paper. In this way the generality of the approach is shown.

The overall modified algorithm is introduced as follows:

(i) If the resultant image, after applying the modified binary mask algorithm, has one ellipse region only, there are no branches and the algorithm should proceed to step (v) directly. Otherwise, if the answer is false, go to step (ii).

(ii) Define the rectangular binary mask based on the pre-defined conditional statement values mentioned above in the preparing stage.

(iii) Check each ellipse region inside of the image by moving the rectangular binary mask over it. If the rectangular binary mask fits with the ellipse shape, the ellipse shape is considered a block crack branch and one should go to step (iv) directly. Otherwise, it is considered to be a main crack and the algorithm should go to step (v) directly. This step must be repeated until all of the ellipse shapes inside the image are completed.

(iv) Check if there is at least one branch in the image. The algorithm will count the total number of branches inside the images and classify them together as a network of cracks (block type), irrespective of the angles of the cracks. The classification procedure will now be completed. The algorithm will compute the area of the block cracks automatically by summation of the areas for all of the block branches inside of the image.

(v) If there are main cracks in the image, the cracks are classified as vertical individual crack, or horizontal individual crack or transverse individual crack based on YING & SALARI (2009). This classification only depends on the orientation angle value (described above on section 3).

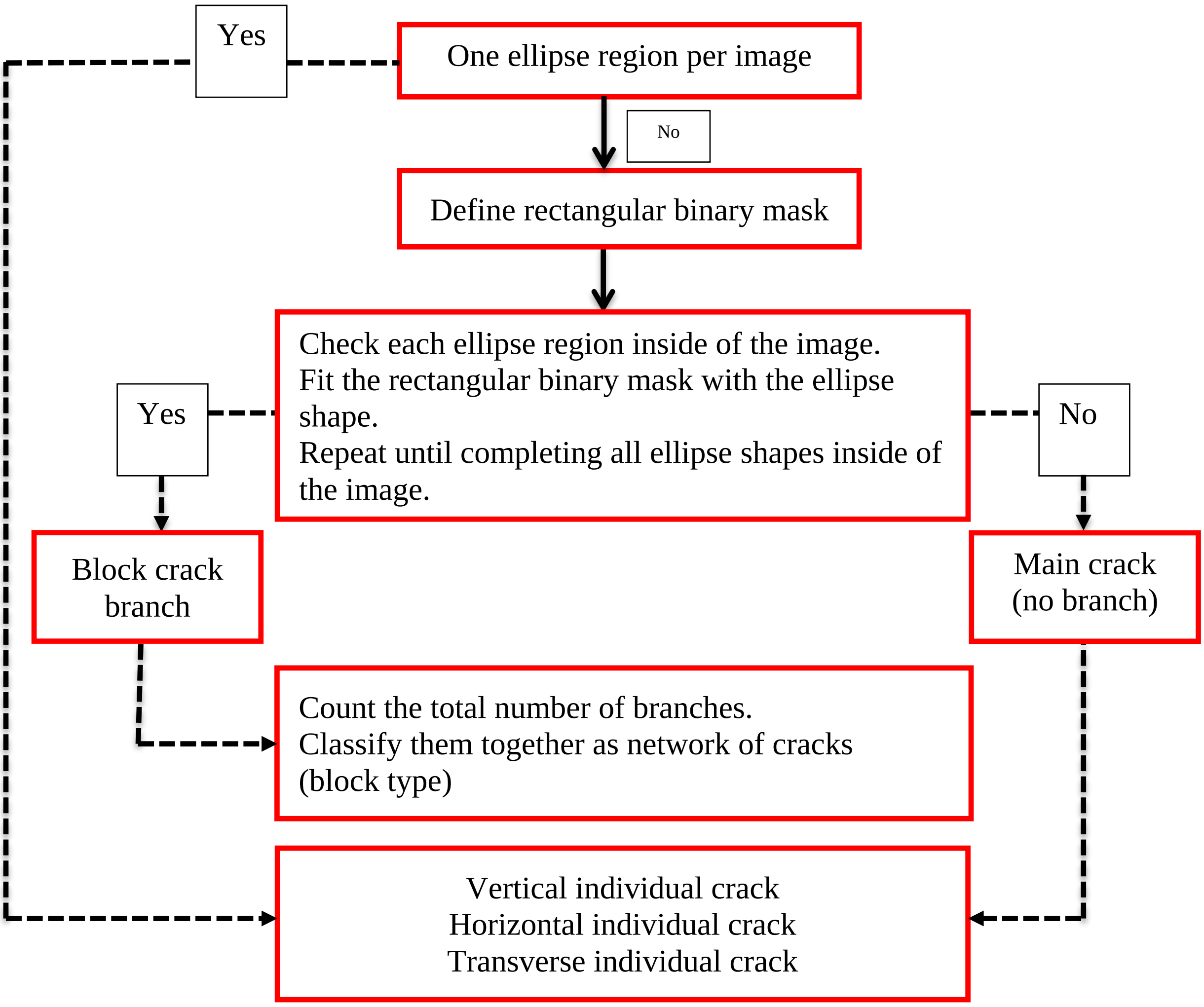

Figure 1 : Workflow for the modified algorithm to classify cracks into different types during detection stage

Inspired by the positive results of using the modified classification algorithm (Figure 2), the latter figure shows that the modified algorithm can determine block crack branches (marked by green rectangular binary mask) correctly, although of its different irregular shapes. This represents a key role to control the classification method. When the rectangle mask fits with the ellipse shape geometrically, the ellipse shape will be considered as a branch, automatically. Moreover, one branch is enough to classify cracks as a network of cracks (block type) without taking orientation into consideration. Otherwise, if the image contains just one ellipse, the individual crack is identified. This assumption is based on the fact that the block crack type must comprise different connected components (branches) with different intensities, colors, and orientations due to their irregular shapes. It is impossible to find block crack that contain just one connected component (one branch equals one ellipse).

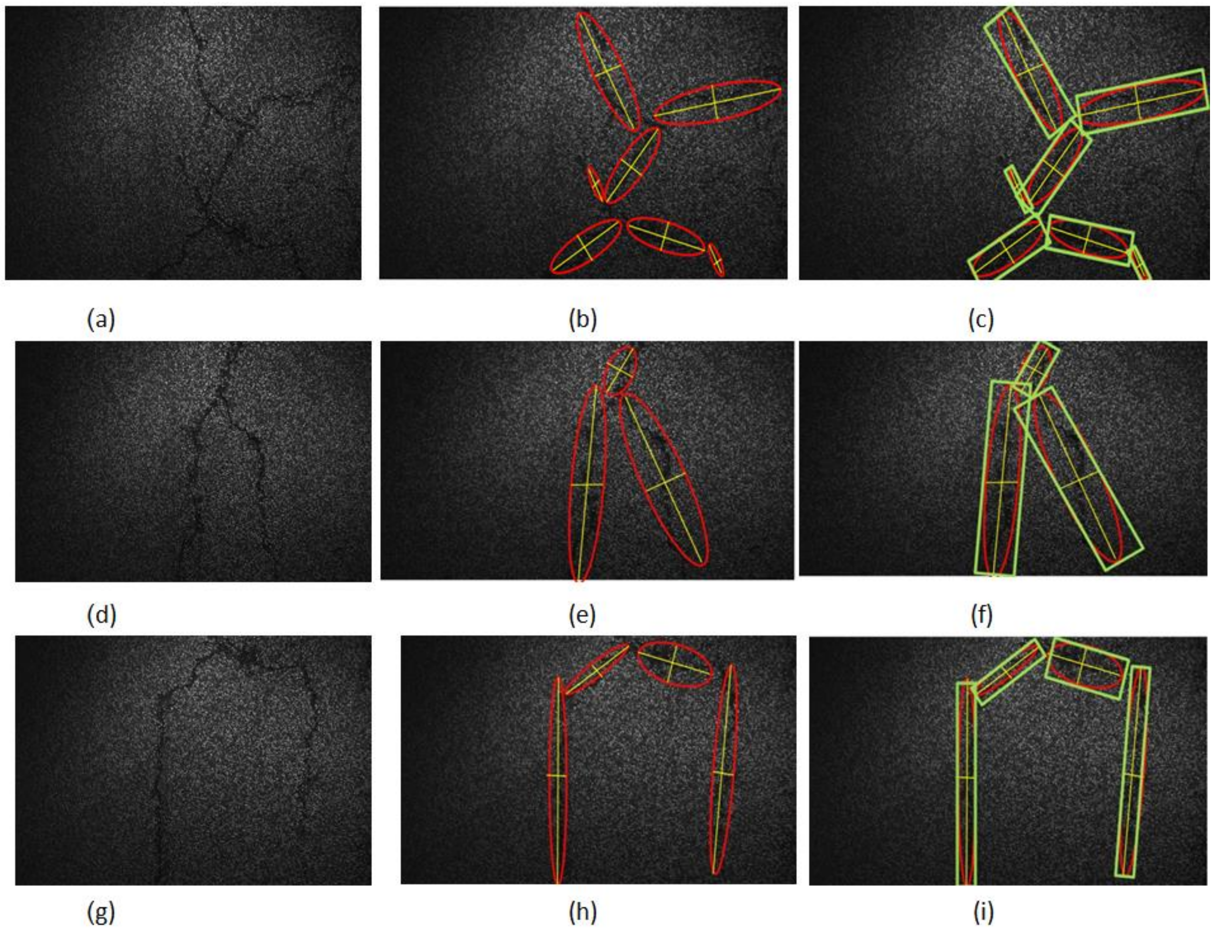

Figure 2: Behavior of the modified algorithm to count the number of block cracks branches within image; the first column represents the original images of block crack type; the second column represents the block crack shape after applying modified binary mask algorithm (AL-MISTARHI&SCHWIEGER 2015); the thrid column represents the block crack shape after moving rectangle binary mask over ellipses regions. The three lines show different examples of block crack types

4. DATA ACQUISITION AND CASE STUDY

Automated survey methods are done using vehicles traveling at highway speeds to gather data. These automated vehicles are called mobile mapping vehicles. Different kinds of automated pavement survey vehicles are obtainable wide world with various data collection techniques. Mobile mapping vehicles consist of different sensors like cameras, laser scanner, inertial measurement unit and lighting unit.

In this paper the sequence pavement images were observed by LEHMANN + PARTNER GmbH company using S.T.I.E.R mobile mapper system. The S.T.I.E.R measuring vehicle is a system for surveying the longitudinal and transverse evenness. It measures texture and 3-dimensional road surface. This system records surface images. It is certified by the German Federal Highway Research Institute (Note: there is no abbreviation for S.T.I.E.R, it is an artificial name) (LEHMANN+PARTNER 2014). This S.T.I.E.R mobile mapper system consists of different sensors with different specifications as follows: (i) Macro picture cameras (Surface cameras) (two in the rear) which take "nearly orthofotos" with a very small overlapping, resolution (1920 x 1080) pixels, every image pixel equals 1.2 mm; (ii) Fraunhofer Institute Lider, 900 points per transverse profile; (iii) Applanix POS LV 420 positioning system (Combination of POS-LV positioning system); (iv) Lighting unit (LEHMANN+PARTNER 2014).

5. CASE STUDY OF THIS REASEARH WORK

5.1 Case study description

To achieve the objectives of this study, the same case study images of mobile mapping data from LEHMANN + PARTNER GmbH company are investigated, that have been used before by AL-MISTARHI & SCHWIEGER (2015) for crack detection objectives. The modified classification algorithm was tested for this data set.

This case study contains 96 sequence pavement images. The length of this case study is 100 m on the street ground. The pavement images of this case study have a resolution of 1920 x 1080 pixel. Every image pixel equals 1.2 mm per ground point. Generally the images of this case study contain: cracks with various shapes, noisy pavement texture, lane markings, tire marks, stop lines, repaired road, skid markings, railways trucks, grates, sidewalk (curbs), manholes covers, signs on the ground, oil spot on the ground, line stripping, lighting columns, water pipelines, traffic loops and bicycles, lighting conditions changing with shadows, shades from road traffic, persons, trees and different illumination conditions. The developed algorithm was applied to this case study. The aim was to classify cracks automatically for all sequence images together without human interaction. Table 1 depicts a description of the dataset for this case study.

Category	Quality
Number of images	96 images
Number of crack images	50 images
Number of vertical crack images	18 images
Number of horizontal crack images	2 images
Number of transverse crack images	10 images
Number of network cracks (Block type)	20 images
Number of non-crack images	46 images
Length of vertical cracks for all images (m)	18.9 m
Length of horizontal cracks for all images (m)	1.7 m
Length of transverse cracks for all images (m)	7.3 m
Area of network cracks (Block type) for all images (m^2)	0.57 m^2

Table1:Description of the dataset for this case study

5.2 Evaluation Criteria

Quality model: For the evaluation of any algorithm one needs a quality model. A quality model is defined as the degree to which a set of inherent characteristics fulfil requirements ((DIN EN ISO 9000 2005). The quality characteristics are concretised by quality parameters to measure the quality by real empirical values.

The developed simple quality model of this paper not only evaluates and judges the quality of the data but also optimizes the quality of the algorithm workflow (process). Therefore, the quality model of this paper will distinguish between the quality of the process and quality of the product The following Figure 3 presents the structure of the quality model for crack detection and classification.

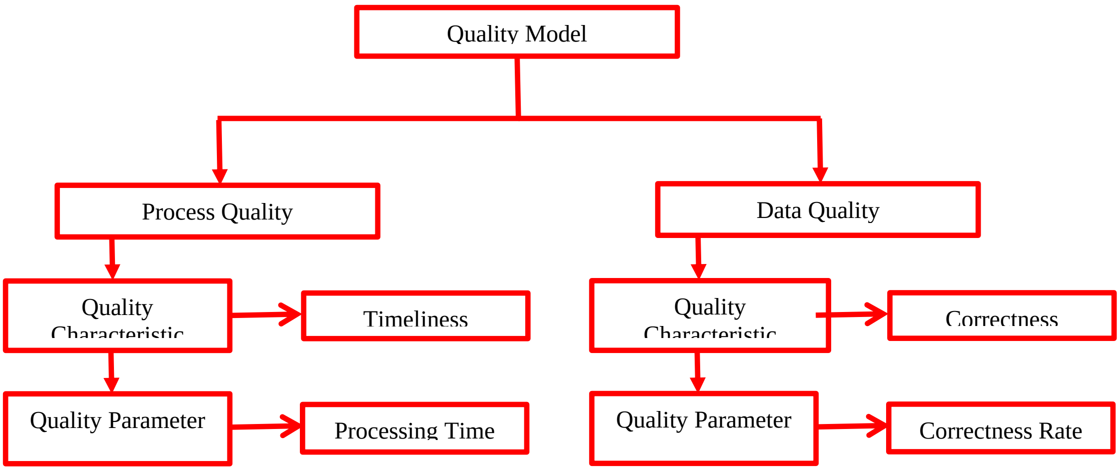

Figure 3: Structure of the quality model for the detection and classification cracks

Process quality is defined as a quality for complete algorithm process. **Process related quality characteristics** include among others timeliness (WILTSCHKO 2004). In this work, the timeliness is defined as the time which the algorithm needs to detect and classify the cracks and its characteristics in the input images and provide the required output. It gives an indication about the algorithm effectiveness. The processing time to complete crack detection and classification is the **process related quality parameter**. It can be calculated using equation:

$$t_p = t_{end} - t_{beg} \text{ ,} \qquad (1)$$

t_p : processing time to complete crack detection and classification [s],
t_{end} : time at the end of the algorithm process [s],
t_{beg} : time at the beginning of the algorithm process [s].

Data quality in general is defined as a quality of incoming data (input), and of outcoming results (output or product quality). **Product related quality characteristics** include among others correctness. The correctness is defined as degree of adherence of existence of information (feature(s), attributes, functions, relationships) to corresponding elements of the reality (WITSCHKO & KAUFMANN 2005). In this work, **Product related quality characteristics** include four parameters for correctness. These four parameters are correctness rate for correct detected individual vertical cracks, for correct detected individual horizontal cracks, for correct detected individual transverse cracks and for correct detected network of cracks (block) cracks. These parameters are defined and calculated using equation (2). Table 2 displays the indices for determining the correctness rates of equation (2).

$$B_i = \left(\frac{M_i}{S_i} * 100\right) \text{ ,} \qquad (2)$$

B_i : correctness rate of the object entity (%),
M_i : number of correct identified object entities,
S_i : total number of the object entities,
i : indices for determining the correctness rate (i=1, 2, 3, 4).

Index (*i*)	Object	Entity
1	Cracks	Correct detected individual vertical cracks in all images
2		Correct detected individual horizontal cracks in all images
3		Correct detected individual transverse cracks in all images
4		Correct detected network of cracks (block) cracks in all images

Table 2: Indices for determining the correctness rate in equation (2).

5.3 Experimental Results and Evaluations

This paper has gained good and promising detection and classification results. Figures 4 and 5 demonstrate some samples and their corresponding results after applying the developed algorithm**.**

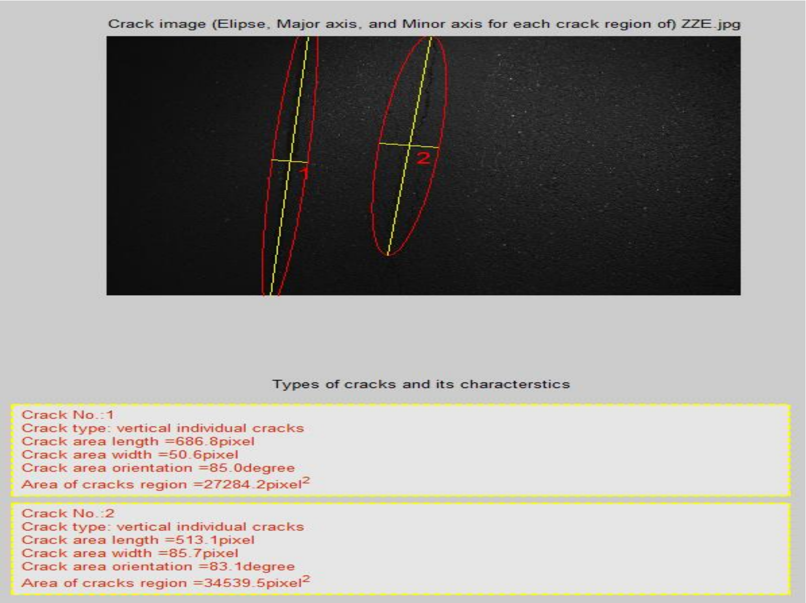

Figure 4: Detected and classified vertical individual cracks

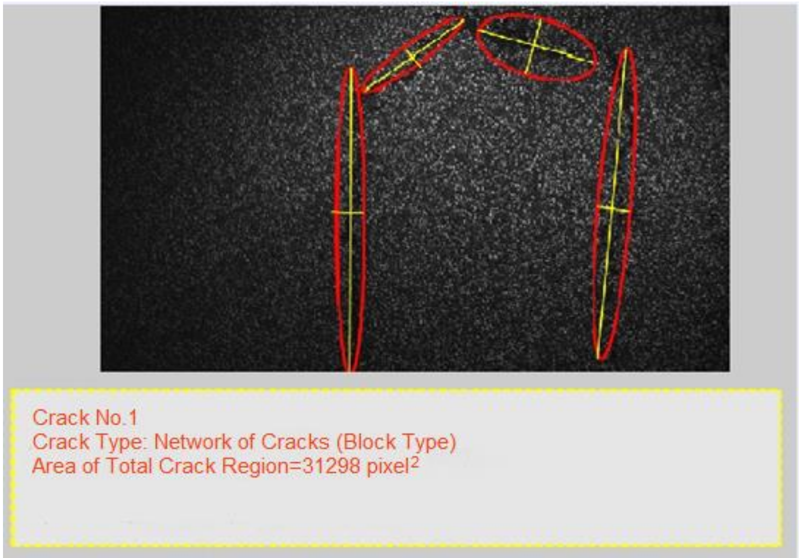

Figure 5: Detected and classified network of cracks (block type)

Figure 4 describes two cracks: the first is a vertical individual crack. Its length equals 686.8 pixel (=0.82m), its width equals 50.6 pixels (=0.06m), its orientation equals 85.0°, and the area of the crack region equals 27284.2pixel^2 (=0.04m^2). While the second is a vertical individual crack Its length equals 513.1 pixel (=0.62m), its width equals 85.7 pixel (=0.10m), its orientation equals 83.1°, and the area of the crack region equals 34539.5 pixel^2 (=0.05m^2). Figure 5 shows the potential of the overall algorithm to detect and classify network of cracks (block type) although of its irregularity shape. The area of the block crack region equals 31298.0 pixel^2 (=0.05m^2). The overall developed algorithm gives a good estimation for cracks properties. This will be important for further maintenance.

The processing time (t_p) for 96 sequence pavement images (1920 x 1080 pixel) is only 3.8 minutes (compare Table 3). Correctness rates of 100%, 100%, 100%, and 100% were achieved for the individual vertical (B_1), horizontal (B_2), and transverse cracks (B_3), as well as the network (block) cracks (B_4), respectively.

Category	Quality
Falsely detected cracks	**0 crack**
Falsely detected images	**0 image**
B_1 **(%)**	**100**
B_2 **(%)**	**100**
B_3 **(%)**	**100**
B_4 **(%)**	**100**
t_p **[s]**	**227.70s≈3.8 min**

Table 3: Results of the Evaluation Process

6. CONCLUSION

This paper has investigated the modified standard classification method to define crack types. Once the cracks are determined in images by the modified binary mask detection algorithm (AL-MISTARHI/SCHWIEGER 2015), the modified standard classification method can be utilized. Moreover the modified classification algorithm can distinguish if the cracks have branches or not. Depending on the existence of crack branches and crack orientation, a decision can be made to classify cracks automatically. Generally the overall developed algorithm can generate a group of ellipse masks in block crack type region. The affected area by the block cracks type are measured by summation the areas for all ellipses inside the block crack region automatically. This will help for further improvements, maintenance, and rehabilitation such as patching for all block crack region.

Experimental results provided in section five have illustrated that the combination between overall developed cracks detection approach by AL-MISTARHI & SCHWIEGER (2015) and the modified standard classification method presented in this paper is an effective algorithm for crack extraction and classification applications. This overall algorithm represents an alternative solution instead of using several softwares of commerical companies for cracks detection and classification applications. In addition the modified standard classification method can overcome the drawbacks previous algorithms in the case of compound block crack classification.

For the test scenario of this paper, the algorithm correctness rates reach 100% for all crack types. In AL-MISTAREHI (2015) additional test scenarios are evaluated. Within these tests, four case studies contain 96, 94, 95, and 96 images, respectively, which were obtained by LEHMANN + PARTNER GmbH Company in Germany. The images of these four case studies have a resolution of 1920 x 1080 pixels. These images contain different types of cracks, lane markings, and lighting conditions. The developed algorithm delivers an average computation time of 3.8 min and the correctness rate is 100% to complete crack classification. In addition, one case study contains 336 different continuous crack images, which were captured by 3D Mapping Solutions GmbH Company in Germany too. The images of this case study have different resolutions with numerous extrinsic objects, such as railways, sidewalks, oil spots, and shadows. The developed algorithm exhibits a correctness rate of 100% in 16.2 min processing time, and classifies the cracks on around 336 continuous mobile mapping images.

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