

Crack identification for rigid pavements using unmanned aerial vehicles

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Abstract. Pavement condition assessment is an essential piece of modern pavement management systems as rehabilitation strategies are planned based upon its outcomes. For proper evaluation of existing pavements, they must be continuously and effectively monitored using practical means. Conventionally, truck-based pavement monitoring systems have been in-use in assessing the remaining life of in-service pavements. Although such systems produce accurate results, their use can be expensive and data processing can be time consuming, which make them infeasible considering the demand for quick pavement evaluation. To overcome such problems, Unmanned Aerial Vehicles (UAVs) can be used as an alternative as they are relatively cheaper and easier-to-use. In this study, we propose a UAV based pavement crack identification system for monitoring rigid pavements' existing conditions. The system consists of recently introduced image processing algorithms used together with conventional machine learning techniques, both of which are used to perform detection of cracks on rigid pavements' surface and their classification. Through image processing, the distinct features of labelled crack bodies are first obtained from the UAV based images and then used for training of a Support Vector Machine (SVM) model. The performance of the developed SVM model was assessed with a field study performed along a rigid pavement exposed to low traffic and serious temperature changes. Available cracks were classified using the UAV based system and obtained results indicate it ensures a good alternative solution for pavement monitoring applications.

1. Introduction

In the last two decades, with the help of developments in high-level processing techniques to extract information from the images and sensing technologies to capture images efficiently and accurately under various lighting conditions, pavement surface monitoring have been brought to advanced levels. Using such superior tools and techniques, the visual examination of pavements becomes now much easier and reliable compared to utilizing conventional methods, which requires massive amount of human work, leading to less accurate analyses and with the potential of producing more biased results.

Technological innovations have helped researchers developing autonomous pavement crack identification systems for flexible pavements. Those developments can generally be grouped in two subfields: (i) automated data collection devices, and (ii) data processing systems. In the first group, data collection systems using either manned or unmanned vehicles are studied for pavement assessment. Fukuhara et al. [1], Klassen and Swindall [2], Wang and Elliot [3], Wang et al. [4,5], Groeger et al. [6], Gavilán et al. [7], Cafiso and Battiatto [8], and Sy et al. [9] focused on developing



two-dimensional imaging systems based on truck mounted cameras. In addition to those, more recent technologies appeared in the literature. Tsai and Li [10] provided insight into the possible use of emerging three-dimensional laser technologies for crack detection studies. Since UAV platforms were successfully utilized in the natural hazards and structural health monitoring applications, they started to be used in transportation applications. For example, Feng et al. [11] performed a real-time road mapping system using UAVs. Zhang and Elaksher [12] presented a UAV based road condition assessment with the help of 3D surface reconstruction methods. Very recently, Zakeri et al. [13] published a quadcopter-based multi stage system to classify pavement distresses. While the above research studies focus more on the development of pavement data collection equipment, in the second group, advances in image processing and machine learning techniques are mainly emphasized. Huang and Xu [14], and Zhou et al. [15] introduced customized, high-speed image processing algorithms to inspect pavement cracks. Nguyen et al. [16] published a method valid for detecting not only cracks but also joints and bridge defects. Li et al. [17], and Zou et al. [18] proposed new methods called FoSa and CrackTree, to detect cracks from images fully-automatically. Recently, Oliveira and Correia [19] presented a method, called CrackIT, for automatic detection and identification of cracks occurring on flexible pavement's surfaces.

Considering that the majority of the above progresses to develop expert level pavement crack identification systems are limited to flexible pavements, there is still a need for applying these technologies to rigid pavements. With this idea in mind, in this paper, we propose a UAV based pavement crack identification system for monitoring rigid pavements' existing conditions based on the combination of image processing techniques and machine learning. In the following section, the method developed is presented. The next section is dedicated to field experiments for validating the proposed technique. Conclusions are given at the end.

2. Method

A pavement crack identification algorithm is proposed in this part. It is independent of data collection tool, i.e., although the images coming from UAVs are used in this study, the algorithm is also able to work with data coming from different sources such as truck vehicles or manually collected pictures. The method consists of two main steps: namely (i) crack candidate detection, and (ii) crack classification. In the first part, images taken by UAVs are segmented such that crack and non-crack bodies are separated from the background image using image segmentation and enhancement techniques. Afterwards, the geometric properties of these bodies are obtained to be used for training of Support Vector Machine (SVM) model. Finally, crack and non-crack regions are classified using the trained SVM model. The details of these two steps are explained in the following sections.

2.1. Crack Candidate Detection

The algorithm starts with an image resizing operation, during which the size of images are reduced to 512x512 pixels to speed up processing time. Then, grayscale transformation operation is performed. Next, with the aim of extracting crack candidate bodies from pavement surface, a thresholding step is utilized. Since it is hard to define a global threshold for segmentation that is valid for all images, each image is considered individually and a manually chosen threshold value is applied. A binary image is then obtained by applying those thresholding values to the image pixel intensities.

The last step for determining crack candidates is the enhancement of binary images including crack and non-crack regions using median filtering and morphological operations. This can be achieved by replacing median of neighbourhood pixels with the center of 3x3 rectangular filter. After applying median filter, some regions other than crack pixels still remain. For this reason, small regions with areas below a pre-set value are removed from the image. These noise removal processes can cause discontinuities in crack bodies. Finally, a morphological closing operation is performed to connect separated crack bodies and enhance the connected regions. As a result, binary images including only crack and non-crack regions are obtained for further processing in the crack classification step.

2.2. Crack Classification

In this part, crack candidate regions are to be grouped into two classes: namely, cracks and non-cracks. To achieve this, a machine learning based approach is followed as geometric properties of crack and non-crack regions differ from each other. For example, longitudinal cracks are thin and vertically long, on the other hand, the width and height ratios of non-crack regions are different. In, non-crack regions covering rectangle are filled with more pixels compared to crack pixels. Properties like these are used as features to train the machine learning based model. Four different geometric properties are defined for crack identification:

- *Extent*: The ratio of bounding rectangle's area that encloses the region to the area of pixels in the region (Figure 1).
- *Aspect Ratio*: The ratio of the distance between leftmost and rightmost point to the distance between upmost and lowermost points, indicated as (w/h) (Figure 1).
- *Eccentricity*: A value that is calculated by dividing the distance between two focus points of the covering ellipse to the length of its major axis (Figure 2).
- *Circularity Ratio*: A value that is computed using the formula given in Equation (1), in which A and P are the area and perimeter of the region, respectively. The value of this measure is 1 for a circular region and $\pi/4$ for a square one.

$$R_c = \frac{4\pi A}{P} \quad (1)$$

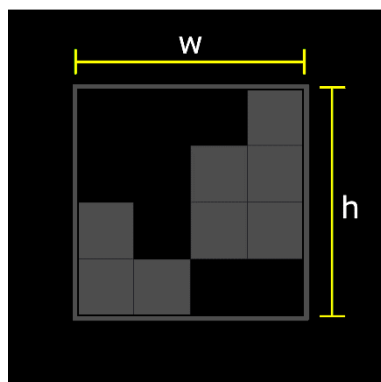


Figure 1. Bounding box and aspect ratio for a given image.

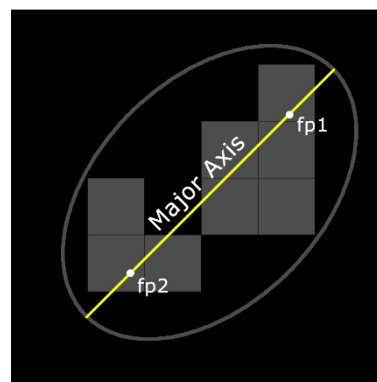


Figure 2. Ellipse covering the region and orientation for a given image.

In the machine learning part, a supervised learning algorithm named Support Vector Machine (SVM) is chosen, since it has performed well in many practical applications. The main idea of SVM is creating decision boundary that separates the classes. The decision boundary, so called, the hyperplane is constructed according to the maximum margin principle, in which the perpendicular distance between data points and the plane are maximized. Briefly, the hyperplane can be formulated by:

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + w_{N+1} = 0 \quad (2)$$

where $\mathbf{w}$ is the normal vector to the hyperplane and $\mathbf{x}$ is the training data, w_{N+1} is the offset and $\mathbf{w}^T$ is the transpose of $\mathbf{w}$. The aim is finding an optimal hyperplane, which is almost equivalently away from nearest data points. The best position of this hyperplane can be found when the margin is largest, which is defined by:

$$\text{margin} = \frac{|1 - w_{N+1}|}{\|\mathbf{w}\|} - \frac{|-1 - w_{N+1}|}{\|\mathbf{w}\|} = \frac{2}{\|\mathbf{w}\|} \quad (3)$$

This provides an optimal training for a classifier. However, it should be kept in mind that every pixel should stay on its correct side when hyperplane separates them. This defines a set of constraints for training in the following manner, where y_i , equals to 1 for class 1 and -1 for class 2.

$$\min \frac{1}{2} \|\mathbf{w}\|^2 \quad \text{such that} \quad y_i(\mathbf{w}^T \mathbf{x}_i + w_{N+1}) - 1 \geq 0 \quad (4)$$

If the above standard quadratic optimization function is solved, the optimal hyperplane orientation can be found. Although this procedure is valid only for linearly separable cases, it can be used for higher order space performing kernel trick transformation. In this study, we selected radial basis function as a kernel. To differentiate crack and non-crack regions, an SVM model is trained using geometric properties mentioned above. While training, the best parameters of SVM are obtained by fivefold cross validation. Finally, the allocated crack candidate regions for testing are classified using the trained model.

3. Experiment and Results

In order to test the performance of the crack candidate detection and classification algorithm, a recent crack data were collected from Middle East Technical University campus rigid pavements. Total of 109 images were taken including crack and non-crack regions using DJI Inspire 1 Quadcopter [20] at different altitudes ranging from 0.5 m to 3 m with a speed of 1 to 3 m/s (Figure 3). Throughout this process, quadcopter's camera was oriented such that it becomes vertical to the surface of the pavement. Pavement images were stored in a micro SD card in the field, then the data processing part was performed in the office.



Figure 3. Data Collection with Drone (METU Campus).

As part of data processing, 157 regions were extracted by applying the crack candidate detection algorithm to a total of 109 pavement photos with 4000 x 3000 pixels resolution. The number of crack candidate regions are greater than the number of photos, because the algorithm is capable of extracting multiple regions from a single image. The results obtained from each step of the algorithm are

illustrated in Figure 4. In the field experiments, out of the 157 regions, 124 of them were labelled crack and 33 were non-crack regions. Afterwards, geometric properties of crack/non-crack regions were calculated. 80% of these regions were allocated for training data set and rest of them were used for the testing. Lastly, crack classification step was carried out through testing of the trained SVM model using this data set.

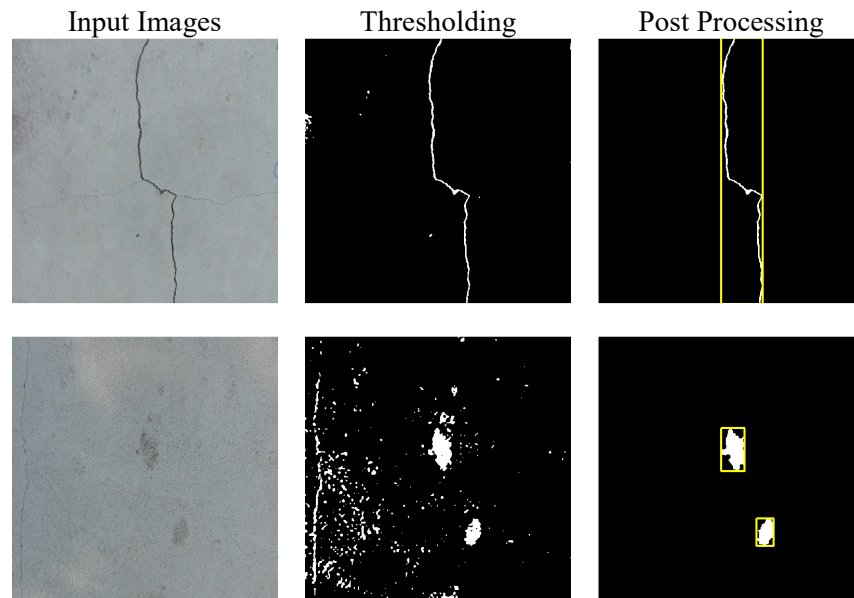


Figure 4. Results of the Algorithm on Crack and Non-crack Regions (Boxes in post processing indicate detected cracks).

Performance estimation of the crack classification algorithm was accomplished by constructing a confusion matrix (Table 1). In this matrix, TP and TN represents the total number of correctly classified and misclassified crack regions, respectively. On the other hand, FP indicates the number of non-crack regions classified as crack and FN denotes the number of crack regions classified as non-crack. Then, most commonly used statistical parameters were calculated using the elements of this matrix.

Table 1. Confusion Matrix.

		PREDICTION	
		Crack	Non-Crack
ACTUAL	Crack	23 (True Positive)	0 (False Negative)
	Non Crack	1 (False Positive)	9 (True Negative)

$$Sensitivity = \frac{TP}{TP + FN} = 100.0\% \quad (5)$$

$$\text{Specificity} = \frac{TN}{TN + FP} = 90.0\% \quad (6)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = 97.0\% \quad (7)$$

According to Table 1, sensitivity metric shows that the proposed algorithm is superior to classify crack regions as cracks. It does not misclassify those cracks as non-cracks either. On the other hand, specificity value is not good as sensitivity, because one of the non-crack regions is misclassified as crack region. For this case, a thin non-crack region mimics the properties of longitudinal crack region. Taking everything into account, the total accuracy of 97.0% proves that the algorithm is successful to distinguish crack and non-crack regions.

In the proposed method, the collected images are in RGB color and do not have any depth information. Some of the non-crack regions intersecting with crack ones prevent the detection of the crack region in the images, because they all appear in the same plane. For instance, shadow and concrete joint spaces cover up or intersect with the crack regions and make them difficult to extract crack bodies from the image. Two examples, illustrated in Figure 5 and Figure 6, were included neither in training data set nor the testing one, since the crack and non-crack regions were not distinguished well. Those kind of noises decrease the performance of the crack detection algorithm.

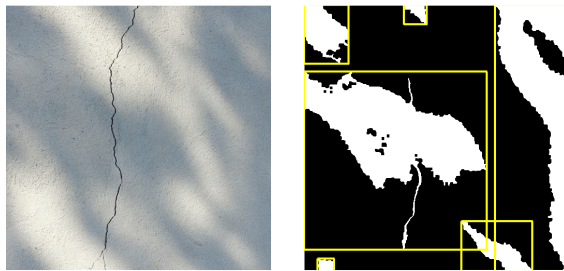


Figure 5. Shadow Included Image.

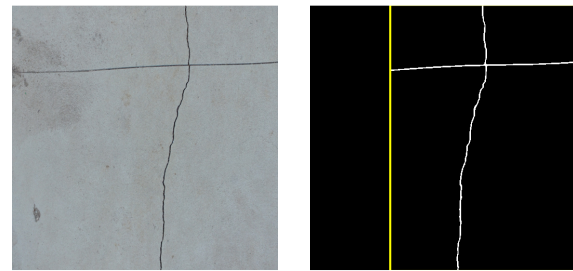


Figure 6. Joint Spacing Included Image.

4. Conclusion

In this paper we propose a pavement crack identification system for monitoring rigid pavements. The system is initialized with images taken by UAVs, which are to be processed using the recently introduced image processing algorithms. Later, distinct features, which are obtained from those images, are used as the inputs of a well-known SVM algorithm for classifying them. The evaluation performance of trained SVM model was measured with a field study performed along a rigid pavement.

The successful results indicate the proposed system ensures a good alternative solution for pavement monitoring applications. Despite some disadvantages such as performance failure in the case of shadowy images or images with low resolution, the main advantage of the system is that, it offers cost-effective solution compared to currently used systems such as truck mounted road monitoring systems as the UAVs are getting cheaper and easily transportable. Meanwhile, the performance of crack detection and classification algorithms should be improved as the performance was tested only with a limited set of data. Within this sense, the future works of this study includes the addition of more features to increase the accuracy of algorithm as well as including additional crack types. After considering safety and flight regulations in the future, the system will have the potential to be used a professional pavement crack identification tool.

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