Pavement information system: detection, classification and compression

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By

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Submitted in partial fulfillment of the requirements for

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An Abstract of

Pavement Information System: Detection, Classification and Compression

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This thesis presents a crack detection and classification algorithm and describes the
procedure of pavement image compression for efficient storage. The algorithm is built
upon wavelet transform. The application of wavelets to images yields different frequency
sub-bands. Also, this algorithm is based on the fact that crack pixels are darker than their
surroundings. The crack detection algorithm decomposes a pavement image into four
sub-bands: one low frequency sub-band called approximation and three high frequency
sub-bands called detail. Cracks appear clearly in the low frequency subband at the first
level through extended pseudo color matrix scaling. The algorithm of classification first
revises and re-computes the horizontal, vertical and diagonal details at the first level
through the energy conservation function, and then forms a new image through adding
corresponding points in the four new sub-bands; finally it applies Radon transform to this
new image. For images compressed for storage, the algorithm combining noise reduction
and compression through wavelet transform is used.
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List of Symbols

\( \psi \)  
- Mother Wavelet

\( \psi_{a,b}(t) \)  
- Child Wavelet

\( \Phi \)  
- Father Wavelet

\( L^2(R) \)  
- Subspaces of the \( L^p \) Function Space

\( x \)  
- Any Function

\( \langle x, \psi_{a,b} \rangle \)  
- Wavelet Coefficient

\( V_i \)  
- Subspace

\( W_i \)  
- Subspace

\( \delta(\cdot) \)  
- Dirac Delta Function.

\( \rho \)  
- Shortest Distance Between Center and Line

\( \theta \)  
- Rotating Angle

\( g(\cdot) \)  
- Radon Transform

\( \zeta \)  
- Parameter
Chapter 1

1 Introduction

This chapter introduces the background, motivation and key contributions presented in this thesis.

1.1 Background

Pavement distress analysis is one of the labor intensive tasks of Departments of Transportation (DOT) around the country. This is because maintenance of ride quality for highway users includes determining pavement repair requirements in a timely fashion on a regular basis. Hence, DOTs across the country employ various strategies to diligently inspect sections of highways, collecting information on pavement conditions and processing it to extract meaningful data.

The traditional human eyes and manual pavement crack detection methods and approaches are expensive, time consuming, dangerous, labor intensive and subjective [1]. In the past two decades, the development of automated pavement inspection systems has been gaining a lot of attention because of high demands for intelligent pavement management strategies.

To get better the pavement images and to process the pavement images are two major concerns existing in an automated pavement inspection system. For the former, imaging sensors, such as video cameras and photomultiplier tubes, are normally used to capture the pavement surface information. As new imaging devices and computers are
developed, it is ever easier to accomplish a real-time screening. The problem lies in the latter, which includes distress detection and isolation, distress image compression and noise reduction, distress classification, distress evaluation, and distress segmentation [2]. To make the right decisions for pavement maintenance, it is critical to develop objective criteria for distress detection, isolation, and evaluation. Over the years, many efforts have been made on this subject with varying degrees of success. Since a huge amount of data is expected to be collected, it is desirable that a rapid screening of pavement surfaces can be performed in real time to detect the existence of distress and to evaluate only those images with distress.

Pavement distresses are a broad category of different anomalous phenomena occurring on pavements. These affect ride quality to different extents. Generally, distresses include cracking, patching and potholes, surface deformation (rutting and shoving), surface defects (bleeding, raveling and so on) and miscellaneous distresses. The Federal Highway Administration has published a Distress Identification Manual that lists the different types of distresses and the characteristics of each [3]. The primary focus of this thesis is on detecting cracks and classifying their types. The major types of cracks are transverse, longitudinal, block and fatigue. Further explanation on each of these is provided in chapter 2. In the next section, the prior performed research and the motivation behind the thesis are presented.

1.2 Motivation for This Thesis

The necessity for automating the process of dealing with pavement images generated by imaging vehicles cannot be overstated. Analysis of the large amount of
images generated by the image collection system manually is impractical and time-consuming. In [4], cracks are manually detected on pavements and the suspect regions are photographed. The images captured are then processed manually using software to segment cracked sections. It is evident that this process would be intractable for implementation on long sections of highways. Moreover, it would also be inconsistent due to operator errors. Hence, to eliminate such a tedious process and improve detection accuracy, researchers have focused their efforts on effective image processing techniques to automatically detect cracks, with minimal or no human interaction.

Recently, Yamaguchi and Hashimoto proposed the use of improved percolation modeling as a technique to detect pavement cracks [5]. However, the process in [5] is not completely automated and may require human interaction to set certain seed parameters.

From an image processing standpoint, there has been emphasis on preprocessing to remove noise while retaining already tested methods of crack detection [6]. The effectiveness of the proposed preprocessing technique was analyzed by testing 50 noisy concrete images. The authors in [6] mainly emphasize preprocessing without considering the variation in pavement roughness. Furthermore, the types of cracks present in the test images have not been provided. Hence, it is uncertain whether this system will perform optimally for all types and extents of cracks.

In another paper, the wavelet based crack detection and evaluation is presented by Zhou et.al [2]. Although their experimental result is well and accurate, its algorithm has high false detection when applied to real pavement images.

Teomete et.al [7], the authors propose the use of histogram projection to identify cracks within a cropped image. Histogram projection is the technique of averaging the
pixel intensities in each row/column and smoothing the difference from a reference gray level. While [7] focused on the severity of cracks, crack classification (in terms of sealed or unsealed), was not performed. Moreover, the system in [7] cannot detect multiple cracks within an image.

In a paper by Bray [8], detection of cracks is performed using a neural network while classification is performed by another neural network. The proposed algorithm has not been tested on real images. The artificially generated images may not yield a good picture of the computational complexity of the algorithm nor of the effectiveness of the technique on real images.

Though there is some commercial system such as WiseCrax developed by Roadware Group Inc. [9] that can perform automated crack detection, their performance cannot be guaranteed. Their images, which eliminate shadows from trees, bridges and tunnels through synchronized strobe lights, are processed offline overnight using advanced image recognition software.

In [10], researchers at Utah State University (USU), in collaboration with the Utah Department of Transportation (UDOT), present a real time automated crack detection and classification system. Here, fuzzy logic has been used to detect distresses followed by a neural network that classifies the distress. It is well known that neural classifiers tend to perform poorly when test data deviates from training data. Therefore, the authors' claim of high classifying accuracy is not well substantiated with a test set of just 42 images in [11].

Additionally, the sensitivity of the approach to variable operating conditions (for example, non-uniform lighting and varying pavement surface roughness) has not been
analyzed. Neural networks have also been applied in [12] to classify pavement distresses. While the training data is artificially generated, the testing data is comprised of both artificial and actual pavement images. However, the number of actual pavement images is not large enough for the conclusive evaluation of the technique.

Therefore, a completely automated crack detection/classification system that can classify all types of cracks is still an open problem. The content described in this thesis pertains to developing such a system and mainly focus on classification. Real pavement images were downloaded from the web. The algorithm developed using wavelet transform and Radon transform concept is presented in the following chapters. The next section presents the key contributions of the thesis, while briefly introducing the steps in the algorithm.

1.3 Key Contributions

This section briefly describes the proposed algorithm and the key contributions of the thesis. The focus of this thesis is on designing an algorithm that can automatically process each pavement image in real time. The major task is to detect, classify cracks in an image, presenting the location, types and severity of the cracks to the end user. Moreover, all types of cracks under different pavement roughness conditions are to be classified with high accuracy.

The proposed algorithm consists of four stages namely (1) detection; (2) mapping; (3) classification, and (4) compression. A flowchart indicating the sequence is shown in Figure 1. The stages in this algorithm are explained in the following chapters.
Figure 1: A Flowchart of the Algorithm
Each test image is processed through the above stages sequentially and the final output image is presented to the end analyst along with the system’s observation on the cracked nature of the image. The key contributions of the thesis are summarized below:

- The proposed algorithm can be used to detect all kinds of cracks.
- The proposed algorithm can be used to classify five types of cracks.
- The mapping stage, described in chapter 4, analyzes the five types of crack and builds the relationship between space domain and radon domain.
- In the classification stage, the technique of Radon transform has been applied to the pavement image. This complete classification algorithm is designed highly based on the relationship in the mapping stage.
- When tested on a large set of real pavement images, the algorithm is found to have a correct detection probability of 97.10% and correct classification probability of 81.12%.

To summarize, this algorithm automates the process of crack detection and classification and pavement image compression. It can be applied on all types of cracks with a high rate of detection and low rate of false classification as well as high compression rate.

1.4 Organization of the Thesis

The rest of the thesis is organized as follows: Chapter 2 introduces the category of cracking phenomena, the data collection equipment and some common protocols of crack evaluation; Chapter 3 describes the theory that will be used in the later chapter; Chapter 4
is the core of this thesis and deals with crack detection and classification, pavement image compression is performed; Chapter 5 represents the experiment result; Finally, Chapter 6 presents the conclusion of the thesis, a summary of its key contributions and future research extensions.
Chapter 2

2 Pavement Inspections and Evaluation

In this chapter, categories of pavement distress and common protocols of pavement distress classification and evaluation as well as pavement image collection system are demonstrated. Image examples for each type of cracking are presented, along with their primary features. Classification of cracks depends on their alignment and structure. Hence, these are the features that will be used by the algorithm to perform accurate classification. A brief explanation of some of the main characteristics of cracks is presented in this chapter. In Section 2.2, the image collection vehicle is presented. Manual recording of pavement distresses by visual inspection is enforcement to the necessity of automation. The performance of the measuring system is of utmost importance to pavement maintenance. This is because inaccurate data collection could introduce artifacts into the images captured, which lead to increased complexities of processing algorithms.

2.1 Types of Pavement Distress

The most commonly seen distresses on pavement surfaces include cracking, rutting, pothole, patching, bleeding, spalling, and surface deterioration. There are five different types of cracking: alligator cracks block cracks, transverse cracks, longitudinal
cracks, and diagonal cracks [13]. Fatigue cracks, also known as alligator cracks are very finely developed patterns that appear as secondary cracking stemming from longitudinal/transverse cracking. These occur as a result of excessive loading and a weakening of the structure beneath the surface. Hence, the cracking described earlier is predominantly surface phenomena while fatigue cracks indicate the beginning of structural damage. Such cracks comprise of finely interconnected web-like cracking that resemble an alligator’s hide [13]. Hence the name alligator crack is associated with this type of cracking. Examples of fatigue cracking are presented in Figure 2. These cracks are different from block cracks.

Block cracks are interconnected cracks that divide the pavement into large rectangular blocks with a size ranging from 3×3 ft to 10×10 ft. For example, the images presented in Figure 3 indicate typical block cracking.
A transverse crack is a crack that is approximately perpendicular to the center line of the pavement, some examples of transverse cracks are presented in Figure 4.

whereas a longitudinal crack is a crack that follows a course approximately parallel to the center line of a pavement and is usually situated at or near the center of wheel tracks, examples of longitudinal cracks are indicated in Figure 5.
A diagonal crack is a crack located at an angle such that it cannot be classified as a transverse crack or a longitudinal crack. It is shown in Figure 6.

All these cracks weaken the pavement and allow water to penetrate, causing further weakening.
Rutting is deformation in wheel tracks caused by load repetitions. The depression can vary from a tenth of an inch to several inches. Potholes are bowl-shaped holes of various sizes in the pavement resulting from localized disintegration under traffic. Rutting and potholes allow water to collect on highway surfaces, which may cause skidding, thus endangering the safety of drivers. Patching represents areas of the pavement that have been repaired with hot or cold asphaltic-concrete mixtures. Bleeding is the presence of free asphalt binder on the pavement surface that is caused by an excess amount of bituminous binder in the mixture. The rate of deterioration of the pavement usually accelerates when any of distresses are present [13].

In the following section, the data collection vehicle and the associated equipment are presented.

2.2 Commercial Implementation

In this section, the image collection vehicle driven along highways to capture pavement images is briefly introduced [9]. Roadware Wisecrax, a commercial crack detection system, collects real-time high-resolution digital pavement images in all lighting conditions at driving speeds. Quality images can be collected at speeds up to 70 mph. The vehicles consist of (1) a pavement camera (downward) system, (2) rack mounted computers, (3) laser sensors, (4) pavement lighting systems, and (5) Global Positioning System. The forward cameras, focusing on the pavement in front of the vehicle, are DVC-1310c digital video cameras with a progressively scanned image format. The downward cameras, mounted in the rear and focusing down on the road surface, are high performance, high-resolution Basler L103 line-scan cameras. Sign cameras are
focused on the side of the road for right of way analysis. The forward and line scan camera computers comprise of 3.0 GHz Pentium IV processors working on Windows 2000 with additional software that synchronize the cameras and lighting. The lighting system consists of ten 150 Watt lamps, each of which has a polished reflector designed for efficient operation. Laser sensors located on the front bumper record the pavement elevation data, generating pavement profiles. The image data recorded using this system is saved on removable hard drives for further analysis.

![Figure 7: The Roadware Wisecracy Vehicle](image)

Roadware claims that its system is able to detect cracks as small as two millimeters. The system is then able to classify the crack either as longitudinal, alligator, transverse or block cracking. However, Roadware’s system also uses synchronized strobe lights to eliminate shadows from trees, bridges, tunnels and other road objects. The usages of high intensity strobe lights will also definitely produce consistent illumination of pavement images and thus making the job of detecting cracks easier.

### 2.3 Protocols of Crack Classification

In the field of pavement distress inspection, many protocols and definitions exist for pavement distress classification and evaluation. One of the most widely used
protocols by many states and agencies is Strategic Highway Research Program Long-Term Pavement Performance (SHRP-LTPP) protocol [14]. SHRP-LTPP first classifies the type of cracks according to their orientations, locations, and shapes and quantifies the severity and extent of the cracks according to their properties, such as width, length, and areas. For a single crack such as a longitudinal, transverse, or diagonal crack, the severity and extent of the crack are measured by the width and length of the crack, respectively. The severity of the block cracks is measured by the total area affected by the cracks. The severity of alligator cracks (so-called fatigue cracks in this protocol) is determined by how the cracks are sealed or spalled, and the extent is also measured by the total area occupied by the cracks. The AASHTO provisional cracking standard (Designation PP44-01) is very similar to SHRP-LTPP. It quantifies the severity and extent according to the width and length or area of the cracks.

Another important protocol is the World Bank’s universal cracking indicator (UCI) [15]. UCI defines a single number to indicate the severity of all the cracks in a pavement segment. For a single crack such as a longitudinal, transverse, or diagonal crack, its indicator is defined as the product of its width and length. For the block and alligator cracks, their indicators are defined by the area that contains the block or alligator cracks. If there is more than one type of crack on a pavement segment, UCI is the sum of indicators for all individual cracks. UCI is finally normalized by the total area of the pavement segment containing cracks. The unified crack index (ASTM STP 1121) is a protocol similar to UCI. The standard crack density can be automatically determined by dividing the number of pixels for the cracks by the number of the total pixels of the pavement segment.
2.4 Summary

In this chapter, different types of distresses generally observed on pavements, along with image examples are presented. Key features of each type of distresses that can be exploited to detect and classify them are also described. In the final section, a description of protocols and definition used for pavement distress classification and evaluation is presented. The equipment of observation system is explained in Section 2.2. In the next Chapter, the theory that will be helpful in understanding the algorithm is introduced.
Chapter 3

3 Theoretical Background

In this section, several theories of techniques that will be used in the later chapters are introduced.

3.1 Wavelet Transform

A wavelet is a waveform of limited duration that has an average value of zero. Unlike sinusoids that theoretically extended from minus to plus infinity, wavelets have a beginning and an end. Wavelets are irregular, of limited duration, and often non-symmetrical. They are better at describing anomalies, pulses, and other events that start and stop within the signal. The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet transform the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions.
3.1.1 Continuous Wavelet Transforms

In continuous wavelet transforms, a given signal of finite energy is projected on a continuous family of frequency bands (or similar subspaces of the $L^p$ function space $L^2(R)$) [16]. For instance the signal may be represented on every frequency band of the form $[f, 2f]$ for all positive frequencies $f > 0$. Then, the original signal can be reconstructed by a suitable integration over all the resulting frequency components.

The frequency bands or subspaces (sub-bands) are scaled versions of a subspace at scale 1. This subspace in turn is in most situations generated by the shifts of one generating function $L^2(R) \in \psi$, the mother wavelet.

The subspace of scale $a$ or frequency band $[1/a, 2/a]$ is generated by the functions (sometimes called child wavelets)

$$
\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left( \frac{t-b}{a} \right)
$$

(3.1)

where $a$ is positive and defines the scale and $b$ is any real number and defines the shift. The pair $(a, b)$ defines a point in the right halfplane $R+\times R$.

The projection of a function $x$ onto the subspace of scale $a$ then has the form

$$
x_a(t) = \int_R \text{WT}_\psi \{x\}(a, b) \cdot \psi_{a,b}(t) db
$$

(3.2)

with wavelet coefficients

$$
\text{WT}_\psi \{x\}(a, b) = \langle x, \psi_{a,b} \rangle = \int_R x(t) \overline{\psi_{a,b}(t)} dt
$$

(3.3)
3.1.2 Discrete Wavelet Transforms

It is computationally impossible to analyze a signal using all wavelet coefficients, so one kind of such system that can sufficiently pick a discrete subset of the upper halfplane to be able to reconstruct a signal from the corresponding wavelet coefficients is the affine system for some real parameters \( a > 1, \ b > 0 \). The corresponding discrete subset of the halfplane consists of all the points \((a^m, na^mb)\) with integers \(Z^2 \ni m, n\). The corresponding baby wavelets[16] are given as

\[
\Psi_{m,n}(t) = a^{-m/2} \psi(a^{-m} t - nb).
\]  

(3.4)

A sufficient condition for the reconstruction of any signal \( x \) of finite energy by the formula

\[
x(t) = \sum\sum \langle x, \psi_{m,n} \rangle \psi_{m,n}(t)
\]

(3.5)

is that the functions \(\{\psi_{m,n} : m, n \in Z^2\}\) form a tight frame of \(L^2(R)\).

3.1.3 Multiresolution Discrete Wavelet Transforms

In any discrete wavelet transform, there are only a finite number of wavelet coefficients for each bounded rectangular region in the upper half plane. Still, each coefficient requires the evaluation of an integral [17]. To avoid this numerical complexity, one auxiliary function, the father wavelet \( \phi \in L^2(R) \) is needed and \( a \) is restricted to be an integer. A typical choice is \( a = 2 \) and \( b = 1 \).

From the mother and father wavelets subspaces is constructed as

\[
V_m = \text{span}(\phi_{m,n} : n \in Z) \quad \text{where} \quad \phi_{m,n}(t) = 2^{-m/2} \phi(2^{-m} t - n)
\]

(3.6)

and
\[ W_m = \text{span}(\psi_{m,n} : n \in \mathbb{Z}) \text{ where } \psi_{m,n}(t) = 2^{-m/2} \psi(2^{-m} t - n). \] (3.7)

From these, the sequence

\[ \{0\} \subset \cdots \subset V_1 \subset V_0 \subset V_{-1} \subset \cdots \subset L^2(R) \] (3.8)

forms a multiresolution analysis of \( L^2(R) \) and the subspaces \( W_1, W_0, W_{-1}, \ldots \) are the orthogonal "differences" of the above sequence, that is, \( W_m \) is the orthogonal complement of \( V_m \) inside the subspace \( V_{m-1} \).

A function in \( V_1 \) can be decomposed into a function in \( V_0 \), that is, a function that is a linear combination of the scaling function at resolution 0, and a function that is a linear combination of translates of a mother wavelet. Since the set of functions that can be obtained by a linear combination of the translates of the mother wavelet as \( W_0 \), this can be written symbolically as [17].

\[ V_1 = V_0 \oplus W_0 \] (3.9)

In other words, any function in \( V_1 \) can be represented using functions in \( V_0 \) and \( W_0 \). Once a scaling function is selected, the choice of the wavelet function cannot be arbitrary. The wavelet that generates the set \( W_0 \) and the scaling function that generates the sets \( V_0 \) and \( V_1 \) are intrinsically related.

If the function can only be accurately represented at resolution \( j+1 \), \( W_j \) as the closure of the span of function, then formula can be showed as

\[ V_{j+1} = V_j \oplus W_j \] (3.10)

But, as \( j \) is arbitrary

\[ V_j = V_{j-1} \oplus W_{j-1} \] (3.11)

And
\[ V_{j+1} = V_{j-1} \oplus W_{j-1} \oplus W_j \]  
(3.12)

Continuing in this manner, for any \( k \leq j \)
\[ V_{j+1} = V_k \oplus W_k \oplus W_{k+1} \oplus \cdots \oplus W_j \]  
(3.13)

In other words, if a function belongs to \( V_{j+1} \) (i.e., that can be exactly represented by the scaling function at resolution \( j+1 \)), it can be decomposed into a sum of functions starting with a lower-resolution approximation followed by a sequence of functions generated by dilations of the wavelet that represent the leftover details. This is very much like subband coding. A major difference is that, while the subband decomposition is in terms of sines and cosines, the decomposition in this case can use a variety of scaling functions and wavelets.

### 3.2 Radon Transform

Radon transform utilizes a set of projections at different angles in an image \( f(x, y) \). The resulting projection is the sum of the intensities of the pixels in each direction, i.e. a line integral [18]. The result is a new image.

#### 3.2.1 Definition of Radon Transform

The Radon transform can be defined in many different ways, on a more general form the linear Radon transform can be defined as follows [19]:
\[
\bar{g}(\zeta_0, \zeta_1, \zeta_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) \delta(\zeta_0 x - \zeta_1 y - \zeta_2 y) \, dx \, dy
\]  
(3.14)

where \( \delta(\cdot) \) is the Dirac delta function.

On this form, the line is described with three parameters, which is one to many to describe a line, so the three parameters should always have a link, which removes one
Since function \( g(x, y) \) has no preferred orientation, this can lead to describe the line as

\[
\rho = x \cos \theta + y \sin \theta
\]  
(3.15)

where \( \zeta_0, \zeta_1, \zeta_2 \) represent \( \rho, \cos \theta, \sin \theta \) respectively.

Thus the linear Radon transform can be rewritten as

\[
\tilde{g}(\rho, \theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) \delta(\rho - x \cos \theta - y \sin \theta) dx dy
\]  
(3.16)

Often another equivalent way of writing is used

\[
\tilde{g}(\rho, \theta) = \int_{-\infty}^{\infty} g(\rho \cos \theta - s \sin \theta, \rho \sin \theta + s \cos \theta) ds
\]

\[
= \frac{1}{|\sin \theta|} \int_{-\infty}^{\infty} g(x, \frac{\rho}{\sin \theta} - x \cot \theta) dx
\]

\[
= \frac{1}{|\sin \theta|} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) \delta(y - \frac{\rho}{\sin \theta} + x \cot \theta) dx dy
\]  
(3.17)

where the s-axis lies along the line.

The meaning of the normal parameters used to specify the position of the line is shown in Figure 8. The parameter \( \rho \) is the shortest distance from the origin of the coordinate system to the line, and \( \theta \) is the angle corresponding to the angular orientation of the line [20].

![Figure 8: Two Parameters \( \rho \) and \( \theta \) Used to Specify the Position of the Line](image_url)
All lines in the normal Radon transform can be described by choosing that $0 \leq \theta \leq 2\pi$ and $\rho \geq 0$, but often other limits are used. If negative values of $\rho$ are introduced, the parameter domain are bounded by

$$0 \leq \theta \leq \pi \quad \text{and} \quad -\rho_{\text{max}} \leq \rho \leq \rho_{\text{max}}$$

where $\rho_{\text{max}}$ is positive and finite when any discrete implementation is considered. Both limitations of the parameter domain are valid, and they can be achieved by following conversion:

$$\tilde{g}(\rho, \theta) = \tilde{g}(-\rho, \theta + \pi)$$

which is easily found using the fact that the delta function is even.

### 3.2.2 The $(\rho, \theta)$ Radon Transform of a Line

One of the major advantages of Radon transform is its application in line detection. Modeling a line with certain parameters $(\rho^*, \theta^*)$ with the delta function gives

$$g(x, y) = \delta(\rho^* - x\cos\theta^* - y\sin\theta^*) \rightarrow$$

$$\tilde{g}(\rho, \theta) = \int_{-\infty}^{\infty} \delta(\rho^* - (\rho \cos \theta - s \sin \theta)\cos\theta^* - (\rho \sin \theta + s \cos \theta)\sin\theta^*) ds$$

$$= \int_{-\infty}^{\infty} \delta(\rho^* - \rho \cos(\theta - \theta^*) + s \sin(\theta - \theta^*)) ds$$

$$= \int_{-\infty}^{\infty} \frac{1}{|\sin(\theta - \theta^*)|} \delta\left(\frac{\rho^* - \rho \cos(\theta - \theta^*)}{\sin(\theta - \theta^*)} + s\right) ds$$

$$= \frac{1}{|\sin(\theta - \theta^*)|}$$

(3.20)

And if $\theta = \theta^*$, i.e., $\sin(\theta - \theta^*) = 0$, it is found that
\[
\tilde{g}(\rho, \theta) = \int_{-\infty}^{\infty} \delta(\rho^* - \rho) \, ds = \begin{cases} 
0, & \text{if } p^* \neq p \\
\int_{-\infty}^{\infty} \delta(0) \, ds, & \text{if } p^* = p 
\end{cases}
\]

(3.21)

the result is that a peak is formed, when \( \rho = \rho^* \) and \( \theta = \theta^* \).

### 3.3 Image Compression

When speaking of a compression technique or compression algorithm, there are actually referring to two algorithms which are the compression algorithm that takes an input \( X \) and generates a representation \( X_c \) that requires fewer bits, and a reconstruction algorithm that operates on the compressed representation \( X_c \) to generate the reconstruction \( y \).

#### 3.3.1 Compression Technique

Based on the requirements of reconstruction, data compression schemes can be divided into two broad classes: lossless compression schemes, in which \( Y \) is identical to \( X \), and lossy compression schemes, which generally provide much higher compression than lossless compression but allow \( Y \) to be different from \( X \).

A compression algorithm can be evaluated in a number of different ways. Usually, the relative complexity of the algorithm, the memory required to implement the algorithm, how fast the algorithm performs on a given machine, the amount of compression, and how closely the reconstruction resembles the original are measured.

A very logical way of measuring how well a compression algorithm compresses a given set of data is to look at the ratio of the number of bits required to represent the data
before compression to the number of bits required to represent the data after compression. This ratio is called the compression ratio. Another way of reporting compression performance is to provide the average number of bits required to represent a single sample. This is generally referred to as the rate [17].

In lossy compression, the reconstruction differs from the original data. Therefore, the efficiency of a compression algorithm is determined by quantifying the difference. The difference between the original and the reconstruction is often called the distortion [17]. Other terms that are also used when talking about differences between the reconstruction and the original are fidelity and quality. For example, the high fidelity or quality of a reconstruction is the same meaning as the difference between the reconstruction and the original is small.

3.3.2 Modeling and Coding

While reconstruction requirements may force the decision of whether a compression scheme is to be lossy or lossless, the exact compression scheme we use will depend on a number of different factors. Some of the most important factors are the characteristics of the data that need to be compressed. A compression technique that will work well for the compression of text may not work well for compressing images. Each application presents a different set of challenges.

The development of data compression algorithms for a variety of data can be divided into two phases. The first phase is usually referred to as modeling [17]. In this phase we try to extract information about any redundancy that exists in the data and describe the redundancy in the form of a model. The second phase is called coding [17]. A description of the model and a "description" of how the data differ from the model are
encoded, generally using a binary alphabet. The difference between the data and the model is often referred to as the residual. There are a number of different ways to characterize data. Different characterizations will lead to different compression schemes.

### 3.4 Pseudo Color

A pseudo-color image is derived from a greyscale image by mapping each pixel value to a color according to a table or function. A familiar example is the encoding of altitude using hypsometric tints in physical relief maps, where negative values (below sea level) are usually represented by shades of blue, and positive values by greens and browns. Pseudo-coloring can make some details more visible, by increasing the distance in color space between successive gray levels. Pseudo-coloring can be used to store the results of image elaboration; that is, changing the colors in order to ease understanding the image. Alternatively, depending on the table or function used, pseudo-coloring may increase the information contents of the original image, for example adding geographic information, combining information obtained from infra-red or ultra-violet light, or MRI scan.

Pseudo-color images differ from false-color images in that they are made from only one original gray-scale image, rather than two or three. A color image is usually represented by three functions of space. In most color formats, the three functions are for three primary colors such as red, green and blue \( f_r(x, y), f_g(x, y), \) and \( f_b(x, y) \), or some other three parameters such as intensity, hue and saturation, \( f_i(x, y), f_h(x,y), \) and \( f_s(x,y) \).

Sometimes artificial colors can be assigned to a gray level image to better distinguish visually the different gray levels.
The display of gray level, pseudo-color and true-color images on a monitor screen through color-map (color lookup table) is illustrated below [21]:

![Diagram showing the display of gray level, pseudo-color, and true-color images](image)

**Figure 9: Schema of Pseudo Color**

![Diagram showing the display of true color](image)

**Figure 10: Schema of True Color**
Chapter 4

4 Method

The proposed method is to use existing image processing techniques such as wavelet transform and Radon transform. There are four major steps in the proposed method: the crack detection, mapping, crack classification and image compression. Wavelet transform is the initial detection to segment a distress in the image. The second step is to build the relationship between wavelet domain and Radon domain. The third step is to classify the crack based on the patterns of peaks in the Radon domain. The final step is to compress the image using wavelet decomposition.

4.1 Crack Detection

In this stage, true color pavement image is firstly transformed into grey scale image, then applying discrete 2-D wavelet transform[22] using db2[23] wavelet at level one to this grey scale image to yield four sub-bands namely, HH, HL, LH and LL. The notion behind this process is firstly filter each row and then down sampling to obtain two \( N \times \frac{M}{2} \) images from an N x M image. Then filter each column and subsample the filter output to obtain four \( \frac{N}{2} \times \frac{M}{2} \) images. Of the four subimages, the one obtained by low-pass filtering the rows and columns is referred to as the LL image; the one obtained by
low-pass filtering the rows and high-pass filtering the columns is referred to as the LH image; the one obtained by high-pass filtering the rows and low-pass filtering the columns is called the HL image; and the subimage obtained by high-pass filtering the rows and columns is referred to as the HH image. This decomposition can be represented as shown in Figure 11.

Figure 11: Decomposition of an Image

Matrix in the high frequency subband, which represents distress is most likely transformed into the high amplitude wavelet coefficients while matrix in the same frequency subband, which represents noise, is more likely transformed into low-amplitude wavelet coefficients. Matrix that represents background in the low frequency subband, is transformed into high amplitude wavelet coefficients. Reconstruct approximation coefficients in matrix LL and combine the horizontal, vertical, and diagonal details in the wavelet domain using energy conservation function to yield wavelet modulus $M_k(x, y)$. This can be explained by equation below:

$$M_k(p, q) = \sqrt{HL_k^2(p, q) + LH_k^2(p, q) + HH_k^2(p, q)}$$
Where $\text{HL}_k(p, q)$, $\text{LH}_k(p, q)$, $\text{HH}_k(p, q)$ are the wavelet coefficients in the horizontal, vertical, and diagonal sub-bands at the position of $(p, q)$ and at the $k$th level. Since distress is mostly transformed into the wavelet coefficients in the high frequency subbands at the first level, $k$ is chosen to be 1.

Since distress is mostly transformed into the wavelet coefficients in the high frequency subbands at the first level, $k$ is chosen to be 1.

This wavelet modulus is used for later crack evaluation stage, the high values of the wavelet modulus represent distress, whereas low values represent noise and background on pavement surface; Finally, extended pseudo color matrix scaling is performed to reconstruct the approximation matrix. This gives a new image with apparent cracks. Thus detect the crack.

\subsection*{4.2 Mapping Between Cracks and Peaks}

The task in the second stage is to build the relationship between the peaks and cracks. Since radon transform basically accentuates the linear features in the wavelet modulus by integrating wavelet coefficients along all possible angles and the location and the number of the cracks are consistent after being transformed from the space domain to the wavelet domain, the peaks in the radon domain can correspond to the cracks in the space domain.
To better understand the relationship, different types of typical cracks are simulated by considering black lines on a gray background, as shown on the left side of the figures. The right side of the figures below show their corresponding radon transform. The angle of a crack is defined as the angle between the direction of the crack and lateral direction of the pavement.

From Figure 13, it can be seen that a peak at 90° in the radon transform indicates a transverse crack on a pavement, and the x coordinate of the peak determines the position of the crack. Similarly, a peak at 0° in Figure 14 indicates a longitudinal crack, and a peak at 135° in Figure 15 or 45° in Figure 16 indicates a diagonal crack at 45° and 135°, respectively. For block and alligator cracks, the number of the peaks increases to at least four. Block cracks form two groups of peaks located at 0° and 90°, respectively. A peak array is defined as having at least two peaks at a certain angle. For the block cracks shown in Figure 17, there should be one peak array at 0° and another one at 90°. For the alligator cracks, there are a peak array at 50° and another at 130°, as shown in Figure 18. In summary, if there are two or three peaks, the cracks are the combined single cracks of the longitudinal, transverse, or diagonal crack. If there are four or more peaks, one needs to determine first whether they form the patterns. If they do, this indicates the existence of block or alligator cracks. If they do not, the cracks are still the combined singular cracks [24].
Figure 13: Transverse Crack and Its Radon Transform

Figure 14: Longitudinal Crack and Its Radon Transform

Figure 15: Diagonal Crack at 45° and Its Radon Transform
Figure 16: Diagonal Crack at 135° and Its Radon Transform

Figure 17: Block Crack and Its Radon Transform

Figure 18: Alligator Crack and Its Radon Transform
Generally, the number of peaks corresponds to the number of cracks, and the number can be used to determine the type of cracks as a single crack or multiple cracks. From the principle of radon transform, it is known that the position of the peaks can be easily used to classify the orientations and locations of the cracks. There are two coordinates, θ and x, for a peak. The angle of the projection, θ, is perpendicular to the orientation of a crack. Therefore, θ is used to classify a single crack as a longitudinal, transverse, or diagonal crack. The coordinate x is the shortest distance between the center and the crack and it is used to locate the position of a crack. From radon transform, it is also known that the wider the crack, the larger the peak. The area of the crack can be used to determine the width of the crack and can be further used to determine the severity of a crack. Since radon transform integrates the crack along its dominant orientation, the peak value has a strong relationship with the length of a crack. The overall mapping between crack and peak is summarized as below:
<table>
<thead>
<tr>
<th>Pattern of Peaks</th>
<th>Position</th>
<th>Number</th>
<th>Position</th>
<th>Area</th>
<th>Peak Value or Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Properties of cracks</td>
<td>Longitudinal</td>
<td>Left lane edge</td>
<td>Crack width</td>
<td>Crack length or crack area</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Transverse</td>
<td>Right lane edge</td>
<td>Low</td>
<td>Occasional</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Diagonal</td>
<td>Lane Center</td>
<td>Medium</td>
<td>Frequent</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Block</td>
<td>Left wheelpath</td>
<td>High</td>
<td>extensive</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Alligator</td>
<td>Right wheelpath</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Relationship Between Crack and Peak

4.3 Crack Classification

This phase describes the classification of new detected cracks by Radon transform. Two important parameters, the number and the position of the windows, are considered for crack classification. The position includes the angle $\theta$ and location $x$ of the center of the window. Since peaks in the radon domain are related to the cracks in the space domain and crack in the real images will not be exactly a line like what the simulation shows above, the classification algorithm is explained in detail as follows:

Firstly, a threshold is needed to determine whether there is a peak. A threshold can be selected by setting peaks search range between $(0.6*p)$ and $(p)$. Here, $p$ represents the radon transform maximum value. After a threshold is selected, a search for the peaks is performed. If a peak is found and other peaks is located close to this peak and the difference of their $x$ value is no more than 15, then all these peaks will be clustered in a window, the number of the windows is increased by one, and the position of the window
center is recorded. The process continues until all the peaks are found and are grouped into windows. The procedure for crack classification is summarized as follows:

1). If the number of windows is equal to one, there is a single crack. If $1^\circ < \theta < 10^\circ$ or $145^\circ < \theta < 180^\circ$, this may indicate the presence of longitudinal crack; else if $35^\circ < \theta < 80^\circ$, this may indicate the presence of obtuse angle diagonal; similarly, if $80^\circ < \theta < 100^\circ$, this may indicate the presence of transverse cracks, otherwise it may indicate the presence of acute angle diagonal crack.

2). If the number of windows is equal to two or three, there are two or three cracks, classify each of them according to Step 1.

3). If the number of windows is equal to four and two of the windows are located between $(1^\circ, 10^\circ)$ and $(145^\circ, 180^\circ)$ and the other two between $80^\circ$ and $100^\circ$, the cracks are block cracks. Otherwise, return to Step 1 to classify them as four single cracks.

4). If the number of windows is equal to or larger than five, there are more likely to be block cracks or alligator cracks. Go to Step 3 to determine whether there are block cracks. If there are two windows array is not located in the ranges of $(1^\circ, 10^\circ)$ and $(145^\circ, 180^\circ)$ or $(80^\circ, 100^\circ)$, there are alligator cracks.

5). If the number of windows is larger than 10, there are most likely alligator cracks.

### 4.4 Image Compression

In this section, the image compression method is presented. The notion behind compression is based on the concept that the regular signal component can be accurately
approximated using a small number of approximation coefficients (at a suitably selected level) and some of the detail coefficients.

The compression procedure is composed of three steps: 1. Decomposition; 2. Detail coefficient thresholding and 3. Reconstruction. In step 2, a threshold is selected for each level from 1 to 3, and hard thresholding is applied to the detail coefficients.

The entire compression procedure is accomplished by two functions named ddencmp and wdencmp applying to the gray scale pavement image. Ddencmp function gives all necessary default values for compression and wdencmp performs compression process of image using the parameters generated by ddencmp. After that, parameters such as percentage of zeros in reconstruction image called the compression performance and percentage of energy recovery are automatically calculated.

The detail of two functions is expressed as follows:

\[
[\text{THR}, \text{SORH}, \text{KEEPAPP}, \text{CRIT}] = \text{ddencmp} \left(\text{IN1}, \text{IN2}, \text{X}\right)
\]

This function returns default values for compression, using wavelets, of matrix X, here is two-dimensional image. THR is the threshold, SORH is for soft or hard thresholding, KEEPAPP allows you to keep approximation coefficients (when it equals to 1), IN1 is 'cmp' for compression. IN2 is 'wv' for wavelet.

\[
[\text{XC}, \text{CXC}, \text{LXC}, \text{PERF0}, \text{PERFL2}] = \text{wdencmp}('gbl', \text{X}, '\text{wname'}, \text{N}, \text{THR}, \text{SORH}, \text{KEEPAPP})
\]

Wdencmp is a two-dimensional compression-oriented function. It performs compression on an image. This function returns a compressed version XC of input image X (two-dimensional) obtained by wavelet coefficients thresholding using global positive threshold THR.
Additional output arguments \([\text{CXC}, \text{LXC}]\) are the wavelet decomposition structure of \(\text{XC}\). \(\text{PERF0}\) and \(\text{PERFL2}\) are L2-norm recovery and compression score in percentage. \(\text{PERFL2} = 100 \times \left(\frac{\text{vector-norm of CXC}}{\text{vector-norm of C}}\right)^2\) if \([\text{C}, \text{L}]\) denotes the wavelet decomposition structure of \(\text{X}\). Wavelet decomposition is performed at level \(N\). \('\text{wname}'\) is the wavelet name. \(\text{SORH ('s' or 'h')}\) is for soft or hard thresholding. If \(\text{KEEPAPP} = 1\), approximation coefficients cannot be thresholded, otherwise they are subject to it.
Chapter 5

5 Testing and Results

The images in this thesis are downloaded from the web with true color. A crack is composed of sets of pixels darker than pixels belonging to the surroundings. To better test the correction of the algorithm, pavement images will contain any type of the cracks such as longitude, traversal, diagonal, block or alligator cracks.

When selecting a wavelet, it is desirable that this wavelet could rapidly detect the crack and only segment the crack. To give best result, a number of wavelets have been tested on various pavement images. In this thesis, Daubechies wavelet with an order two is used.

This section shows the result of the proposed method in detecting different type of crack.
5.1 Visual Results

Figure 19: Experiment 1

(a) Grayscale Image

(a) Wavelet Decomposition

(a) Detected Crack

(a) Radon Transform

(a) Number of Windows

Table 2: Classification of the Image (a)

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>$\theta$</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5°</td>
<td>Longitudinal</td>
</tr>
</tbody>
</table>
Figure 20: Experiment 2

(b) Grayscale Image

(b) Wavelet Transform

(b) Detected Crack

(b) Radon Transform

(b) Number of Windows

Table 3: Classification of the Image (b)

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>81°</td>
<td>Traversal</td>
</tr>
</tbody>
</table>
Figure 21: Experiment 3

(c) Grayscale Image

(c) Wavelet Transform

(c) Detected Crack

(c) Radon Transform

(c) Number of Windows

Table 4: Classification of the Image (c)

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>70°</td>
<td>Diagonal at 135°</td>
</tr>
</tbody>
</table>
Figure 22: Experiment 4

(d) Grayscale Image

(d) Wavelet Transform

(d) Detected Crack

(d) Radon Transform

(d) Number of Windows

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>55°, 58°, 60°, 105°, 130°, 150°</td>
<td>Alligator</td>
</tr>
</tbody>
</table>
Figure 23: Experiment 5

(e) Grayscale Image

(e) Wavelet Transform

(e) Detected Crack

(e) Radon Transform

(e) Number of Windows

Table 6: Classification of the Image (e)

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>$\theta$</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>90°</td>
<td>Traversal</td>
</tr>
</tbody>
</table>
Figure 24: Experiment 6

(f) Grayscale Image

(f) Wavelet Transform

(f) Detected Crack

(f) Radon Transform

(f) Number of Windows

Table 7: Classification of the Image (f)

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>0°, 80°~120°, 160°~180°</td>
<td>Alligator</td>
</tr>
</tbody>
</table>
Figure 25: Experiment 7

(g) Grayscale Image

(g) Wavelet Transform

(g) Detected Crack

(g) Radon Transform

(g) Number of Windows

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>80°, 90°</td>
<td>Composite</td>
</tr>
</tbody>
</table>
Figure 26: Experiment 8

(h) Grayscale Image

(h) Wavelet Transform

(h) Detected Crack

(h) Radon Transform

(h) Number of Windows

Table 9: Classification of the Image (h)

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>90°, 130°, 180°</td>
<td>Composite</td>
</tr>
</tbody>
</table>
Figure 27: Experiment 9

(i) Grayscale Image
(i) Wavelet Transform

(i) Detected Crack
(i) Radon Transform

(i) Number of Windows

Table 10: Classification of the Image (i)

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8°</td>
<td>Longitudinal</td>
</tr>
</tbody>
</table>
Figure 28: Experiment 10

(j) Grayscale Image

(j) Wavelet Transform

(j) Detected Crack

(j) Radon Transform

(j) Number of Windows

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>90°</td>
<td>Traversal</td>
</tr>
</tbody>
</table>
Table 12: Classification of the Image (k)

<table>
<thead>
<tr>
<th>Number of Windows</th>
<th>θ</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0°~20°, 100°~140°, 160°~170°</td>
<td>Alligator</td>
</tr>
</tbody>
</table>
5.2 Statistical Results

To test the success rate of the propose method, a set of 30 images with different types of cracks is chosen for the experiment, there are 21 images containing cracks and 9 images containing no crack. For crack detection, whether or not the result is successful or fail based on the comparison between the result and the original image, the crack must be exactly the same as the original one and no noise existed in the result image. For crack classification, the successful result would be the same as description of classification algorithm. For pavement image compression, if the compression rate of a image is greater than 50% and the original image looks the same as the corresponding reconstructed one, then this compression is successful.

The crack detection algorithm is able to achieve 97.10% of successful detection. The 2.90% failures may be due to the noise from background or the crack is too thin to detect.

The crack classification algorithm is able to achieve 81.1% of success of knowing the types of crack in the image. For the remaining 18.9%, the algorithm still misclassifies the cracks that are presented in those images. The failures may be due to the inconsistent lighting condition, image containing no crack and much more complicated types of crack.

Image compression using wpdencmp and ddencmp two functions can achieve high compression rate and reconstructed image is nearly the same as the original one, the percentage of zeros is around 51% and the percentage of energy recovery is around 99%.
Chapter 6

6 Conclusion

In the previous chapter, the experimental result of crack detection, classification and image compression is presented. In this chapter, the key contributions of this work are summarized. Finally, future work to extend this thesis is identified.

6.1 Summary of Key Contributions

In this thesis, pavement distress detection and classification algorithm as well as pavement image compression algorithm is proposed. The technique of wavelet transform is applied to decompose an image into sub-band level for the later stages of crack detection and image compression. This technique is followed by radon transform, which is used for crack classification. The proposed method is very robust for crack detection, classification and image compression. The results showed that the proposed method can detect and classify all types of cracks, such as transverse cracks, longitudinal crack, diagonal cracks, block cracks, and alligator cracks. The results also showed that the proposed method has a high success rate.

Since a peak in the radon domain is related to a crack in the space domain, the patterns of a peak, such as the number, position, peak value and area, are used to classify the type and quantify the severity and extent of distress. The number of windows can be used to classify a single crack or multiple cracks. The horizontal coordinate of a window
is used to classify the type of a crack as longitudinal, transverse, or diagonal. The vertical coordinate is used to determine the position of a crack and further the extent of the crack.

### 6.2 Future Work

The future focus of this thesis is presented below:

- This thesis mainly presents the crack detection and classification, puts little emphasis on image compression. Since image storage is also an important factor in pavement management system especially when we need to face millions of images. This work may also be extended to include more advanced compression algorithm to efficiently and largely reduce the storage space.

- The conversion of the platform used to implement the algorithm from Matlab to C would improve the computational time greatly. Hence, this conversion is a potential expansion to the thesis.

- Using a technique for analysis of pavement profile data such that it is effective on various sections of the highway would be an important development. Integrating this technique with the information from the image processing algorithm would present self-validating results to the end analyst, reducing much of the labor otherwise involved in manually analyzing images and profiles simultaneously.

- Invoking software such as Google Map at the end of the algorithm can present geographical locations along the Ohio Streets and Highways where cracking is present.
This will make the entire algorithm have more functionality and lead to a quite flexible pavement management system.
References


[19] "http://petertoft.dk/PhD/"


Appendix

Matlab Code

clear all

%input image

e=imread('3.jpg');
d=rgb2gray(e);
imshow(d)
title('pavement cracking image')

%wavelet transform
[ca,ch,cv,cd]=dwt2(d,'db2');
figure,imshow(wcodemat(ca,192))
colormap(pink);
title('detected crack')

size(ca);
y=wcodemat(ca,192);
[q,w]=size(y);
for i=1:q
    for j=1:w
        if (y(i,j)>=30)
            y(i,j)=0;
        else
            y(i,j)=1;
        end
    end
end

% radon tranform
% and location of the crack

theta=1:180;
[r,xp]=radon(y,theta);
figure,imagesc(theta,xp,r)
colormap(hot); colorbar
title('random of crack')
size(r)
th=zeros(1,180);

% show crack severity
peak=max(max(r))
peak_min=0.6*peak;
[h,v]=size(r);
for i=1:h
    for j=1:v
        if (r(i,j)<=peak&&r(i,j)>=peak_min)
            r(i,j)=1;
        else
            r(i,j)=0;
        end
        th(1,j)=j;
    end
end
figure, imagesc(theta,xp,r)
% type of crack
l=0;
dia3=0;
dia4=0;
t=0;
for j=1:180
    if (th(1,j)>1&&th(1,j)<=35)
        disp('This is longitude crack')
        l=l+1;
    elseif(th(1,j)>35&&th(1,j)<=80)
        disp('This is diagonal 135 degree crack')
        dia3=dia3+1;
    elseif(th(1,j)>80&&th(1,j)<=100)
        disp('This is traverse crack')
        t=t+1;
    elseif(th(1,j)>100&&th(1,j)<=145)
        disp('This is diagonal 45 degree crack')
        dia4=dia4+1;
    elseif(th(1,j)>145&&th(1,j)<=180)
        disp('This is longitude crack')
        l=l+1;
    end
end
l
dia3
dia4
t
% image compression for storage
i=double(e);
Xrgb=0.2990*i(:,1)+0.5870*i(:,2)+0.1140*i(:,3);
NbColors=255;
X=wcodemat(Xrgb,NbColors);
map=pink(NbColors);
figure
image(X),title('pavement cracking image')
colormap(map),colorbar
whos;
[c,s]=wavedec2(X,2,'bior3.7');
A1=wrcoef2('a',c,s,'bior3.7',1);
A2=wrcoef2('a',c,s,'bior3.7',2);
H1=wrcoef2('h',c,s,'bior3.7',1);
V1=wrcoef2('v',c,s,'bior3.7',1);
D1=wrcoef2('d',c,s,'bior3.7',1);
H2=wrcoef2('h',c,s,'bior3.7',2);
V2=wrcoef2('v',c,s,'bior3.7',2);
D2=wrcoef2('d',c,s,'bior3.7',2);
figure,colormap(map);
subplot(2,4,1); image(wcodemat(A1,255))
title('Approximation A1')
subplot(2,4,2); image(wcodemat(H1,255))
title('Horizontal Detail H1')
subplot(2,4,3); image(wcodemat(V1,255))
title('Vertical Detail V1')
subplot(2,4,4); image(wcodemat(D1,255))
title('Diagonal Detail D1')
subplot(2,4,5); image(wcodemat(A2,255))
title('Approximation A2')
subplot(2,4,6); image(wcodemat(H2,255))
title('Horizontal Detail H2')
subplot(2,4,7); image(wcodemat(V2,255))
title('Vertical Detail V2')
subplot(2,4,8); image(wcodemat(D2,255))
title('Diagonal Detail D2')

% compression through wavelet

[thr,sorh,keepapp]=ddencmp('cmp','wv',X);
[Xcomp,cx,lc,perf0,perf2]=wden cmp('gbl',c,s,'bior3.7',2,thr,sorh,keepapp);
figure,colormap(map);
subplot(121);image(X);title('Original image');
axis square
subplot(122);image(Xcomp);title('Compressed image');
axis square
% measurement of compression
perf0
perf12