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Evaluation of digital imaging systems used in highway applications

Alex Mraz

University of South Florida

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Evaluation of Digital Imaging Systems

Used in Highway Applications

by

Alexander Mraz

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
Department of Civil & Environmental Engineering
College of Engineering
University of South Florida

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DEDICATION

This dissertation is dedicated to my parents Ludovit and Zlata, my brother Michal, and my friends Mary and Roy. Without their help and comprehension, I could never have reached where I am today.
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EVALUATION OF DIGITAL IMAGING SYSTEMS
USED IN HIGHWAY APPLICATIONS

Alexander Mraz

ABSTRACT

Manual pavement condition surveys are gradually replaced by more comprehensive automated surveys conducted by multi-function highway evaluation vehicles. Highway evaluation vehicles are generally equipped with laser profiling, land navigation, and imaging sub-systems. The imaging system consists of three cameras; forward-view and side-view digital area-scan cameras for capturing images of traffic signs and right-of-way safety features, and a pavement digital line-scan or area-scan camera for capturing images of the pavement surface. In addition to the 3-laser and accelerometer-based profiling system, these vehicles are also equipped with differential global positioning equipment (DGPS) and an inertial measurement unit (IMU) for cross-slope, curvature and grade measurements.

Digital imaging systems installed in automated highway evaluation vehicles are generally designed on modular basis where subsystems by different manufacturers are assembled to customize the system and fulfill the users’ needs while minimizing the cost. In most such cases, manufacturers’ specifications for a subsystem would not be reliable with respect to the eventual performance of that subsystem as part of the entire assembly.
On the other hand, no guidelines are available for performance evaluation of imaging systems as assemblies of discrete subsystems. Moreover, images acquired by digital cameras can become contaminated by random noise affecting their quality and the ability of identifying important features. These issues have surfaced during the development and testing of the Florida Department of Transportation (FDOT) highway evaluation vehicle. This first phase of the work involved in this dissertation research concerns the study of basic criteria for evaluation of image quality through measurement of well-defined properties of images such as color reproduction, tone reproduction, detail reproduction, as well as the levels of noise, and optical distortion. Standard and reliable methods that can be adopted for evaluation of the above properties are discussed first. Then, by applying the above evaluation criteria to the imaging systems of the FDOT highway evaluation vehicle, it is shown how the sources of images sub-quality can be recognized and the optimum settings achieved.

The second phase of the dissertation research is focused on the investigation of the sources of noise that can affect the digital line-scan distress images. As a result of this study, a novel technique was developed to filter out noise present in pavement distress images by using intensity measurement obtained from a standard grayscale target. In addition, a detailed experimental study was conducted to investigate the effect of the speed of evaluation and lighting conditions on the accuracy and repeatability of digital line-scan images in representing the actual distress condition of a pavement. The conclusions drawn from second phase can be used to minimize the effect of noise on digital images of pavement distress and to improve the accuracy of evaluation of
pavement cracks based on digital images. Hence the results of this study will certainly enhance the overall efficiency of the automated evaluation of pavement distress and highway features.
CHAPTER 1
EVALUATION OF PAVEMENT DISTRESS AND HIGHWAY FEATURES USING DIGITAL IMAGING

1.1 Development of the FDOT Highway Evaluation Vehicle

Until recently, the Florida Department of Transportation (FDOT) has used forward-view images of the highway network, which were made available on a three-year cycle through a Consultant. In May of 2000, a study was conducted to explore potential improvements to FDOT’s videolog program (Dougan, 2001) which resulted in the following recommendations:

1. increasing the frequency of video-logging,
2. upgrading the scale of image acquisition to obtain right-of-way data from outer or center lane and condition data from the pavement, and
3. creating a department-wide unit to manage the consolidated image and field data acquisition, processing, storage and retrieval operations.

Hence, a research project was initiated to explore a fully automated exhaustive evaluation operation that includes adding the following functionalities to existing imaging in the forward direction:

1. imaging in the right-of-way mode to identify up-to-date roadway features that also include safety related features such as bridge and railroad crossing identification, edge line of pavements and images of ramps,
(2) imaging in the downward direction,
(3) global positioning for location referencing of the collected data,
(4) acquiring roadway cross-slope data, and
(5) collecting pavement roughness and rut data for pavement distress evaluation.

It was envisioned that the above objectives could be achieved by using a profiler van equipped with a video camera system for imaging in forward, sideward, and downward directions, an inertial measurement unit for collecting pavement cross-slope data, and a Differential Global Positioning System (DGPS) equipment for data geo-referencing purposes.

At present, pavement evaluation crews of FDOT and several other Department of Transportation (DOT) conduct “windshield” surveys at relatively slow speeds to identify the types of surface cracking and other distresses on pavements. In addition to this, when necessary, they have to be physically present in a travel lane to take manual rut measurements, exposing themselves to hazardous conditions. Pavement imaging can preclude the need for conducting hazardous surveys, especially on high speed facilities. On the other hand, pavement images which provide a permanent record of the pavement surface condition can be used to evaluate and analyze data using the desktop computer and also to perform a quality control of the “windshield” survey pavement evaluation data.

As the first task of the research project, in April 2002, International Cybernetics Corporation (ICC) in Largo, Florida manufactured the highway evaluation vehicle commonly referred to as the Florida Department of Transportation (FDOT) Highway
Evaluation Vehicle (Figure 1.1). This digital image data collection system consists of forward-view, side-view, and pavement digital imaging systems (ICC 2000). Moreover, this vehicle is also equipped with the Applanix Position Orientation System (POS), consisting of Differential Global Position System (DGPS) and an Inertial Measurement Unit (IMU), capable of delivering accurate and instantaneous information about the position, speed, and orientation of the vehicle, as well as the grade and curvature of the roadway. Furthermore, the vehicle is capable of obtaining longitudinal profiling (IRI) data through a laser accelerometer system mounted on the front bumper of the highway evaluation vehicle.

Figure 1.1 FDOT Highway Evaluation Vehicle

1.1.1. Forward-View and Side-View Imaging Systems

The FDOT highway evaluation vehicle uses two high resolution (1300 x 1024 pixels) digital area-scan cameras for forward-view and side-view images at a rate up to 12 frames per second enabling video capture at highway operating speeds of up to 75
mph. The forward-view camera (Figure 1.2) captures the panoramic view of the road while the side-view camera is set up to obtain the side-view right-of-way data. These cameras are mounted in a Pelco enclosure with a fan and a heater to protect them from environmental effects. The forward-view camera uses a C-mount lens with a 16.5 mm focal length while the side-view camera uses a C-mount lens with a 25 mm focal length.

The forward-view imaging system is used to record the highway inventory features such as pavement markings, number of lanes, permanent roadway signage in front of the vehicle, work zones, traffic control and data collection devices. Side-view imaging system is used to specifically record the roadway signs and maintenance and safety features.

![Forward-View Camera](image)

**Figure 1.2 Forward-View Camera**

### 1.1.2. Pavement Imaging System

The pavement (downward-view) imaging system of the FDOT highway evaluation vehicle consists of a Basler L-103 line-scan camera (Figure 1.3) with Sigma Fisheye lens of focal length of 15 mm, controlled by a Windows 2000 operational system.
and ICC LineScan capturing software. The pavement camera is mounted 9.25 ft over the pavement surface providing the ability to capture an area with a width and length of 14.5 ft and 20 ft, respectively. The image created by the capturing software contains 2048 by 2942 pixels respectively, representing the width and length of the captured area. Each image is built-up of 2942 image lines captured separately and combined together to create one image. Each image line can be captured in preset exposure times of 1/19,000 or 1/40,000 second depending on the lighting conditions.

To ensure good quality images of the pavement during the short period of time each image line is captured by minimizing the effect of the shadow cast on the visibility of the pavement features such as cracks. To enable pavement survey in the night time, FDOT highway evaluation vehicle is equipped with a built-in pavement lighting system shown in Figure 1.4. The pavement lighting system consists of ten polished reflectors, each containing a 150 Watts lamp.

Figure 1.3 Pavement Camera
1.1.3. Position and Orientation System

Global Position System (GPS) is an excellent positioning system, especially for slow moving vehicles in open areas. However, in road survey one cannot afford the occasional loss in position data caused by blocked satellites, and one requires data updated more frequently than is possible with current receiver technology. In many of these cases, the requirement can be met with integration of an inertial system which can update information at a frequency of 200 Hz or higher. Use of inertial technology to measure position and orientation has a number of advantages, especially for moving vehicles. It provides high accuracy irrespective of vehicle motion, and is self-contained. However, errors grow over time, making an inertial system best suited for short-term observations only. Thus, inertial systems require an external position fix at the start and end of the vehicle’s run. This provides a geographic context for the system’s
observations. If both systems, GPS and inertial system, are coupled together, regular external position fixes are provided through the GPS unit onboard the vehicle.

The central part of an inertial navigation system is the Inertial Measurement Unit (IMU) which is a self-contained sensor consisting of three silicon accelerometers and three fiber-optic gyroscopes. This sensor is bolted to the vehicle, so that it undergoes the same motion as the vehicle. The accelerometers measure accelerations along each of the three axes, $X$ in the travel direction, $Y$ in the lateral right direction, and $Z$ towards the vehicle’s floorboard. If the IMU’s initial location is known, double integration of the accelerations experienced by the vehicle will yield the vehicle position. Similarly, the three gyroscopes measure the rates of angular rotations about the $X$, $Y$, and $Z$ axes and are used to determine vehicle orientation as well as grade and cross-slope of a road.

In the FDOT highway evaluation vehicle, the above functions are accomplished by a mounted Applanix POS™ LV (Position and Orientation System for Land Vehicles) system which integrates Differential GPS (DGPS) and inertial technologies into one precise position and orientation location system generating a stable, reliable, and repeatable positioning solution that provides the benefits of both systems, while minimizing their shortcomings. The core of an Applanix system shown in Figure 1.5 is the IMU, which provides the inertial solution. The IMU is complemented by two GPS receivers, whose position information serves to provide the inertial solution with position updates, thereby controlling the error growth. If the GPS receiver is unable to provide position information (e.g. due to blocked satellites), the IMU will continue to provide
position and orientation information unaided. Figure 1.6 shows the block configuration of the Applanix system.

Figure 1.5 Applanix POS™ LV System Used in FDOT Highway Evaluation Vehicle

Figure 1.6 Block Diagram of Applanix POS™ LV System in FDOT Highway Evaluation Vehicle

1.1.4. Laser Profiling System

FDOT highway evaluation vehicle is equipped with a profiling system, shown in Figure 1.7 that consists of three laser units, two of which have a sampling frequency of 32 kHz and a third one with a sampling frequency of 16 kHz. The lasers are mounted on
the front bumper and two 32 kHz laser units are positioned above the wheel paths to profile the road surface and evaluate the rut depth. The sensors used in the vehicle are semi-conductor laser diodes that use appropriate optics to project a laser spot on a pavement surface. The reflected laser can be used to determine the vertical distance to the vehicle’s bumper from the pavement.

In order to establish a reference plane from which the profile is measured, an accelerometer has to be used. Thence the vehicle also utilizes a vertical position sensing Jewell LCA-100 Series accelerometer with a sensitivity range of 0.5/g to 10/g. Accelerometer readings can be used to determine the vertical position of the vehicle bumper with respect to the reference plane. Then, the road profile is determined from the numerical difference between the vehicle’s vertical position and the distance between the vehicle body and the pavement surface. Finally, the International Roughness Index (IRI) is computed from the road profile along the left and right wheel paths.

Figure 1.7 Laser Profiling Unit Installed on the Front Bumper
1.2 Overview of Digital Imaging

1.2.1. State-of-the-Art of Digital Imaging

According to Wang (Wang 2000), a common method of imaging pavement surfaces was using the analog format through area-scan cameras. A digitizing process converts the analog–based images, in which analog data is transformed into computer-understandable digital format. Wang (Wang 2000) discusses the advantages of the relatively new digital camera technology.

On the other hand, the line-scan cameras scan one line at a time with a resolution as high as 6,000 pixels per line (2Kx2K) with a data rate of 30 MHz. Captured single lines are then compiled to form a 2-D area for analysis. Although several problems associated with analog area-scan cameras, such as the relatively low resolution and the necessity for digitizing, do not exist with digital line-scan cameras, Wang (Wang 2000) emphasizes the need for higher light intensity in line scan cameras.

For area scanning at highway speeds, the maximum available exposure time is about 60 µs while in line scanning, the maximum available exposure for one line is about 50 µs in order to capture a crack that is less than 2 mm. Since these short exposure times require high illumination intensity, strobe-illuminating devices are effective for area-scan cameras. However, for line-scan cameras, high intensity continuously illuminating devices are needed.

The main difficulty associated with automated survey of pavement surface distress is the rapid rate of data collection and the corresponding extraordinary computational needs, when real-time processing is to be implemented. However, real-
time processing technology is still in development. When a compromise is made with respect to computing performance, both the data quality and performance speed are affected. However this issue is gradually being resolved with the continued development of high speed processors. Wang (Wang 2002) also describes a pavement imaging system that is capable of analyzing automated distress survey data on a real-time basis at speeds of up to 20 mph.

1.2.2. Analog to Digital Conversion

In electronic terms, analog signals contain data over a continuous range. Analog voltage signals represent the intensity or brightness of an image over a given area. However, modern computers can work only with digital data that are represented by discrete numbers. Therefore, the primary function of digital cameras, the schematic diagram of which is shown in Figure 1.8, is to convert analog image intensities into digital values. The process of measuring the intensity values in a continuous image at discrete intervals in space is known as sampling.

Figure 1.8 Schematic Diagram of a Digital Camera
In a digital camera, the image sensor consists of a large number of individual pixels, each of which measures the intensity of light reflected or transmitted from a real scene. Each pixel generates a voltage signal in analog form which is proportional to the amount of the light received. The process that converts the analog signal to digital data is performed by an analog-to-digital converter (ADC). The number of gray levels a given camera can recognize between black and white depends on the type of ADC used in the camera. For example, an 8-bit ADC would allow 256 different levels of intensity values between black and white or pure black, pure white, and 254 different shades of gray in the resulting digital image.

1.2.3. Spatial Resolution

Digital images are composed of pixels and the resolution of a digital image will be largely, but not totally, dependent upon the physical size of a pixel in the image. For a given field of view, dense sampling will produce high resolution images, in which there are a relatively large number of pixels representing a small part of a scene. Spatial resolution dictates the amount of useful information that can be extracted from an image. The effect of the resolution on interpretation of a pavement image is illustrated in Figure 1.9 which displays the same portion of the pavement image at three different resolutions.
To determine the resolution of the imaging sensor in a given direction in terms of the number of pixels per a given distance unit, the total number of the pixels has to be divided by the dimension of the sensor in that direction. For example, Basler L103 line-scan camera used in pavement imaging system of the FDOT highway evaluation vehicle contains a Thomson TH7814A linear sensor which is 20.48 mm wide and comprises of 2048 photosensitive pixels. Then, the maximum attainable resolution on the sensor is 2048/20.48, or approximately 100 pixels per mm.

The rate at which the intensity value changes over an image is measured by the spatial frequency. Rapid changes in intensity are characterized by high spatial frequencies and they can be represented accurately only in a densely-sampled image. Whenever possible, the sampling chosen for a given image must satisfy the Nyquist criterion, which states that the sampling frequency must be at least twice the highest spatial frequency found in the image (Efford 2000). If the image sampling does not satisfy the Nyquist criterion, then the image may suffer from the effect of aliasing. In aliasing, a signal of a certain frequency that has been undersampled can appear at a lower frequency upon
image reconstruction. This obviously has the effect of distorting the signal, introducing frequency components that are unrepresentative of the original signal.

1.2.4. Bit Depth

The bit depth is determined by the number of possible values used to define each pixel. In computing, one bit is the smallest amount of data that can be processed by a computer. A bitonal image made of pixels consisting of one bit each can represent two tones only, which are typically black and white. This image type uses the value zero for the intensity of black color and a value one for the intensity of white color. Then the number of available gray levels would be \( i = 2^b \), where \( b \) represents the bit depth. Accordingly, for black and white imaging, 256 gray levels, or 8 bits, are necessary for the eye to recognize a continuous range of gray tones without any noticeable banding. The comparison of images of the same pavement section at different bit depths is shown in Figure 1.10.

![Figure 1.10 Color Depth of the Pavement Segment. (a) 1-bit (black and white); (b) 4-bit (16 gray levels); and (c) 8-bit (256 gray levels)](image-url)
On the other hand, digital color images are usually composed of three primary colors (red \( R \), green \( G \), and blue \( B \)). In a color image conforming to the RGB model, the color value of a given image pixel is a vector with three components, corresponding to \( R \), \( G \), and \( B \) colors. \( R \), \( G \), and \( B \) can be regarded as orthogonal axes defining a three-dimensional color intensity space where every possible color is mapped onto a point inside the color cube shown in Figure 1.11 (Efford 2000). Eight bits per pixel are required for each of the three colors in order to display continuous tone and a photo-realistic image. Therefore, a single pixel has to have 8 bits each for \( R \), \( G \), and \( B \) colors with a total of 24 bits \((256 \times 256 \times 256 = 2^{24})\), allowing the representation of more than 16.7 millions of color combinations.

![Figure 1.11 The RGB Color Cube](image)
1.2.5. Software Used for Intensity Measurements of Digital Images (ImageJ)

*ImageJ* (Rasband 2004) is a public domain image processing software that is programmed in the *Java* programming environment. It can be executed either as an online applet or as a downloadable application on any computer equipped with *Java* 1.1 or newer virtual machine environment. The main window of the program is illustrated in Figure 1.12.

![ImageJ Main Window](image-url)

*Figure 1.12 Main Window of the ImageJ Image Processing Software*

*ImageJ* program can display, edit, analyze, process, save, and print grayscale or color 8-bit, 16-bit, and 32-bit images. It can read data files in many formats including BMP, JPG, TIFF, GIF, and raw image formats. *ImageJ* program is designed to work as a multi-threading application so that time-consuming operations such as image file reading can be performed in parallel with other operations. The program can simultaneously process a number of images limited only by the available memory.

*ImageJ* program has been designed with an open architecture that provides extensibility via *Java* plugins. Custom acquisitions, analysis, and processing plugins can be developed using *ImageJ*'s build-in editor and *Java* compiler. As a result, user-written plugins can facilitate solutions to almost any image processing or analysis problem. To solve analytical problems related to the images captured by the FDOT highway
evaluation vehicle and to post-process pavement distress images by filtering, a

*PhotoES_AM* plugin was written in *Java* language. The main window of this plugin is shown in Figure 1.13.

![Main Window of the PhotoES_AM Plugin Written for ImageJ Software](image)

1.13 Main Window of the PhotoES_AM Plugin Written for ImageJ Software

The *PhotoES_AM* plugin specifically enables one to measure the Signal-to-Noise Ratio (SNR) of an imaging system based on an image of a standard grayscale target. It also allows a color quality assessments using an image of the Macbeth Color Checker (Figure 2.5) and determination of the Modulation Transfer Function (MTF) (Section 2.6.3) using an image of the bar patterns of a standard resolution target. In addition, it allows the use of local intensity statistics to filter noise out of pavement images to improve their quality.
1.2.6. Storage of Digital Image Data

If the total number of pixels in an image is known, the file size of the uncompressed image $s_{file}$ can be determined as:

$$s_{file} = \frac{p_{total} \times b}{8}$$ (1.1)

where $p_{total}$ is the total number of pixels in the image and $b$ represents the image bit depth. For example, if an image has 1200 x 800 pixels, then from Eqn. (1.1), the size of the image will be 2,880,000 bytes, or 2.8 Mb.

However, the final size of the file that stores an image will be determined by the file format used to save it. Important attributes of five most commonly used formats are listed in Table 1.1. Many formats, such as JPEG or TIFF have compression capabilities which will reduce the size of the stored file. When compressing images, equal consideration must to be given to the file size and the image quality. There are two basic types of compression methods:

(1) lossless – where no information is lost during the compression and decompression processes and the reconstructed image is mathematically and visually identical to its original, and

(2) lossy – where some information is lost during the compression process and based on the degree of compression, the lost information may or may not be noticeable.
Table 1.1 Common Image Formats and Their Attributes (DeMello 2003)

<table>
<thead>
<tr>
<th>Name and Current Version</th>
<th>TIFF 6.0 (Tagged Image File Format)</th>
<th>GIF 89a (Graphics Interchange Format)</th>
<th>JPEG (Joint Photographic Expert Group/JFIF (JPEG File Interchange Format)</th>
<th>JP2-JPX/ JPEG 2000</th>
<th>PDF 1.4 (Portable Document Format)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extension(s)</td>
<td>.tif, .tiff</td>
<td>.gif</td>
<td>.jpeg, .jpg, .jif, .jif</td>
<td>.jp2, .jpx, .j2k, .j2c</td>
<td>.pdf</td>
</tr>
<tr>
<td>Bit-depth(s)</td>
<td>1-bit bitonal; 4- or 8-bit grayscale or palette color; up to 64-bit color</td>
<td>1-8 bit bitonal, grayscale, or color</td>
<td>8-bit grayscale; 24-bit color</td>
<td>supports up to 2\textsuperscript{14} channels, each with 1-38 bits; gray or color</td>
<td>4-bit grayscale; 8-bit color; up to 64-bit color support</td>
</tr>
<tr>
<td></td>
<td>Lossy: JPEG</td>
<td>Lossless</td>
<td>Uncompressed Lossless/Lossy: Wavelet</td>
<td>Loss: JPEG</td>
<td>Loss: JPEG</td>
</tr>
<tr>
<td>Color Mgmt.</td>
<td>RGB, Palette, YC\textsubscript{b}C\textsubscript{r}, CMYK, CIE L<em>a</em>b*</td>
<td>Palette</td>
<td>YC\textsubscript{b}C\textsubscript{r}</td>
<td>Palette, YC\textsubscript{b}C\textsubscript{r}, RGB, sRGB, some ICC</td>
<td>RGB, YC\textsubscript{b}C\textsubscript{r}, CMYK</td>
</tr>
<tr>
<td>Web Support</td>
<td>Plug-in or external application</td>
<td>Native since Microsoft\textsuperscript{®} Internet Explorer 3, Netscape Navigator\textsuperscript{®} 2</td>
<td>Native since Microsoft\textsuperscript{®} Internet Explorer 2, Netscape Navigator\textsuperscript{®} 2</td>
<td>Plug-in</td>
<td>Plug-in or external application</td>
</tr>
<tr>
<td>Metadata Support</td>
<td>Basic set of labeled tags</td>
<td>Free-text comment field</td>
<td>Free-text comment field</td>
<td>Basic set of labeled tags</td>
<td>Basic set of labeled tags</td>
</tr>
</tbody>
</table>

1.2.7. JPEG Compression

Joint Photographic Expert Group (JPEG) was developed during 1980s and made available in 1991. This development is a joint effort by the Consultative Committee on International Telegraphy and Telephony (CCITT) and International Standards Organization (ISO). It was created to define a standard for compressing photographic...
images. JPEG compression technique relies on the fact that human eye is much more sensitive to change of intensity (luminance) in the image than to color (chrominance). The image data are thus separated into luminance and chrominance, and lossy compression algorithms are then applied to the chrominance data only.

JPEG compression is a three-stage process illustrated in Figure 1.15. First, the system divides the image into blocks of 8 by 8 pixels, to which a mathematical transform known as forward discrete cosine transform (FDCT) is applied. Purpose of this is to transform the image from the spatial domain into the frequency domain. This has its basis in Fourier transform used by electrical engineers for analyzing the frequency component of signals. Then, the compression procedure averages 24-bit intensity value (or 8-bit for grayscale image) of every pixel inside the block. This average value is stored in the top left-hand corner of the block and the rest of 63 pixels are assigned values relative to this average.

In the next step, quantization is performed where the values produced by FDCT are divided by values in the quantization matrix. When a quantization matrix with sufficiently high quantizing values is used, many of the values produced by FDCT are reduced to zero resulting in “blocky” appearance in the low frequency part of an image (Figure 3.16). After quantization, the 64 coefficients are prepared for entropy encoding. In this step, previous coefficient is used to predict the current coefficient and the difference is encoded. Then the quantized coefficients are passed to entropy encoding procedure which compresses the data further. Huffman and arithmetic encodings are the encoding procedures implemented into the JPEG compression algorithm because they
produce the most effective compression for a wide range of image types (Davies and Fennessy 2001). During the reordering, most zero values can be represented by a very short piece of computer code (ITU-T 1992).

![Diagram of JPEG compression algorithms](image)

**Figure 1.14 Illustration of JPEG 3-stage Compression Algorithms**

### 1.3 Relationships Used in Optical Analysis

The most important characteristics of a lens are its magnifying power and the light gathering capacity. The magnification factor, \( m \), of the lens can be expressed as (Efford, 2000):

\[
m = \frac{\text{image size}}{\text{object size}} = \frac{v}{u}
\]

(1.2)

where \( u \) and \( v \) are the distances from the lens to the object and the image sensor, respectively.

The power of lens is usually expressed in terms of the reciprocal of its focal length, \( f \), which represents distance from the lens to the point at which parallel incident
rays converge (Figure 1.15). The commonly used relationship between \( u \), \( v \), and \( f \) is as follows (Efford, 2000):

\[
\frac{1}{f} = \frac{1}{u} + \frac{1}{v}
\]

(Figure 1.15 Illustration of the Image, Object, and Focal Length Relationship)

Eqn (1.3) has been used frequently in this dissertation for analysis involving the digital camera optical system.

1.4 An Overview of Pavement Surface Distress

Pavement distress can be classified based on the type of pavement surfaces. Strategic Highway Research Program (SHRP) Distress Identification Manual (SHRP, 1992) recognizes three main types of pavement surfaces. They are asphalt concrete pavements, jointed Portland cement concrete pavements, and continuously reinforced pavements. Types of pavement surface distress based on pavement types are described in Tables 1.2 and 1.3 for asphalt and rigid pavements, respectively.
Table 1.2 Asphalt Concrete Surfaced Pavement Distress Types

<table>
<thead>
<tr>
<th>DISTRESS TYPE</th>
<th>UNIT OF MEASURE</th>
<th>DEFINED SEVERITY LEVELS?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A. Cracking</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Fatigue Cracking</td>
<td>m²</td>
<td>yes</td>
</tr>
<tr>
<td>2. Block Cracking</td>
<td>m²</td>
<td>yes</td>
</tr>
<tr>
<td>3. Edge Cracking</td>
<td>m</td>
<td>yes</td>
</tr>
<tr>
<td>4a. Wheel Path Longitudinal Cracking</td>
<td>m</td>
<td>yes</td>
</tr>
<tr>
<td>4b. Non-Wheel Path Longitudinal Cracking</td>
<td>m</td>
<td>yes</td>
</tr>
<tr>
<td>5. Reflection Cracking at Joints</td>
<td>Number, m</td>
<td>yes</td>
</tr>
<tr>
<td>Transverse Reflection Cracking</td>
<td>m</td>
<td>yes</td>
</tr>
<tr>
<td>Longitudinal Reflection Cracking</td>
<td>Number, m</td>
<td>yes</td>
</tr>
<tr>
<td>6. Transverse Cracking</td>
<td>Number, m</td>
<td>yes</td>
</tr>
<tr>
<td><strong>B. Patching and Potholes</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Patch / Patch Deterioration</td>
<td>Number, m²</td>
<td>yes</td>
</tr>
<tr>
<td>8. Potholes</td>
<td>Number, m²</td>
<td>yes</td>
</tr>
<tr>
<td><strong>C. Surface Deterioration</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Rutting</td>
<td>mm</td>
<td>no</td>
</tr>
<tr>
<td>10. Shoving</td>
<td>Number, m²</td>
<td>no</td>
</tr>
<tr>
<td><strong>D. Surface Defects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11. Bleeding</td>
<td>m²</td>
<td>yes</td>
</tr>
<tr>
<td>12. Polished Aggregate</td>
<td>m²</td>
<td>no</td>
</tr>
<tr>
<td>13. Raveling</td>
<td>m²</td>
<td>yes</td>
</tr>
<tr>
<td><strong>E. Miscellaneous Distresses</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14. Lane-to-Shoulder Dropoff</td>
<td>mm</td>
<td>no</td>
</tr>
<tr>
<td>15. Water Bleeding and Pumping</td>
<td>Number, m</td>
<td>no</td>
</tr>
</tbody>
</table>

Table 1.3 Jointed Concrete Surfaced Pavement Distress Types

<table>
<thead>
<tr>
<th>DISTRESS TYPE</th>
<th>UNIT OF MEASURE</th>
<th>DEFINED SEVERITY LEVELS?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A. Cracking</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Corner Breaks</td>
<td>Number</td>
<td>yes</td>
</tr>
<tr>
<td>2. Durability Cracking (“D” Cracking)</td>
<td>Number, m²</td>
<td>yes</td>
</tr>
<tr>
<td>3. Longitudinal Cracking</td>
<td>m</td>
<td>yes</td>
</tr>
<tr>
<td>4. Transverse Cracking</td>
<td>Number, m</td>
<td>yes</td>
</tr>
<tr>
<td><strong>B. Joint Deficiencies</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5a. Transverse Joint Seal Damage</td>
<td>Number</td>
<td>yes</td>
</tr>
<tr>
<td>5b. Longitudinal Joint Seal Damage</td>
<td>Number, m</td>
<td>no</td>
</tr>
<tr>
<td>6. Spalling of Longitudinal Joints</td>
<td>m</td>
<td>yes</td>
</tr>
<tr>
<td>7. Spalling of Transverse Joints</td>
<td>Number, m</td>
<td>yes</td>
</tr>
<tr>
<td><strong>C. Surface Defects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8a. Map Cracking</td>
<td>Number, m²</td>
<td>no</td>
</tr>
<tr>
<td>8b. Scaling</td>
<td>Number, m²</td>
<td>no</td>
</tr>
<tr>
<td>9. Polished Aggregate</td>
<td>m²</td>
<td>no</td>
</tr>
<tr>
<td>10. Popouts</td>
<td>Number, m²</td>
<td>no</td>
</tr>
<tr>
<td><strong>D. Miscellaneous Distresses</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11. Blowups</td>
<td>Number</td>
<td>no</td>
</tr>
<tr>
<td>12. Faulting of Transverse Joints and Cracks</td>
<td>mm</td>
<td>no</td>
</tr>
<tr>
<td>13. Lane-to-Shoulder Dropoff</td>
<td>mm</td>
<td>no</td>
</tr>
<tr>
<td>14. Lane-to-Shoulder Separation</td>
<td>mm</td>
<td>no</td>
</tr>
<tr>
<td>15. Patch / Patch Deterioration</td>
<td>Number, m²</td>
<td>yes</td>
</tr>
<tr>
<td>16. Water Bleeding and Pumping</td>
<td>Number, m</td>
<td>no</td>
</tr>
</tbody>
</table>
In asphalt pavements, the most common distress types are rutting (Figure 1.16 (a)) and alligator cracking (Figure 1.14(b)) while in rigid pavements, they are corner breaks (Figure 1.17(a)) and panel cracks (1.15(b)). The majority of roads (97%) in the State of Florida are made of asphalt pavements.

Figure 1.16 (a) Alligator (fatigue) Cracking; (b) Rutting on Flexible Pavement

Figure 1.17 (a) Corner Break; (b) Large Panel Crack on Rigid Pavement
1.5 Research Goals

The objectives of this dissertation research are as follows:

(1) using fundamentals of optics to identify the key components of a standard digital imaging system that influence the quality of images,

(2) describe scientific methods of assessing digital imaging systems

(3) layout a systematic methodology to achieve the optimum settings of digital imaging systems,

(4) identify the major noise sources affecting the quality of digital images of pavements,

(5) develop an effective filtering method that uses a standard grayscale target

identify the effects of the speed of the highway evaluation vehicle and lighting conditions on the quality of images, and

(7) uncover any relationship between signal to noise ratio and the ability to recognize cracks from images.

1.6 Organization of the Dissertation

Chapter 2 of the dissertation describes the development of rational guidelines for performance assessment of digital imaging systems. Major sources of noise present in digital images are identified in Chapter 3 and a novel technique is developed for filtering noise in digital images. Then in Chapter 4, the experimental methodology that was setup to investigate the effect of vehicle speed and lighting conditions on the digital images is described and the results are exemplified. And finally in Chapter 5, conclusions based on the research findings are summarized.
CHAPTER 2

GUIDELINES FOR PERFORMANCE ASSESSMENT OF DIGITAL IMAGING SYSTEMS USED IN HIGHWAY APPLICATIONS

2.1 Introduction

State-of-the-art highway evaluation systems have become multi-functional by incorporating combinations of pavement surface roughness sensors, high resolution cameras, inertial measurement units (IMU), DGPS, and distance measurement instrumentation (DMI). Typical information obtained in automated highway evaluation includes data on roadway geometry (horizontal and vertical curvature, longitudinal and transverse profiles), pavement condition (distress) and texture, rutting, and safety features. Evaluation data are stored and archived in formats compatible with data stored in pavement management databases. By associating spatial information from GPS or linear measurements, users can query the system and retrieve information relevant to damage assessment, design, planning and maintenance, location of roadway and roadside assets, selection of locations for traffic-monitoring systems, and quality control and quality assurance (QC/QA).

The images can be used for public hearing presentations, responses to questions raised by public and private individuals, and inspection of sites prior to and after construction. In addition, images collected at regular intervals can be helpful in providing useful historical records for condition assessment, and in facilitating various engineering
evaluations. Hence, imaging of traffic and safety features and pavement distress is a valuable tool for highway asset and pavement management.

Traditional pavement surveys range from a thorough walking survey of 100% of the pavement surface in which all distress types, severities, and quantities are measured, recorded, and mapped to a windshield survey at normal traffic speed in which the rater assigns the pavement a general category or sufficiency rating without identifying individual distress types. In either case, the inspection of the pavement surface is direct and human cognition is used to categorize and determine the type of distress, severity and quantity of distress present on the pavement surface. Overall, manual surveys are considered labor intensive, slow, expensive, and sometimes unsafe. They also invariably involve a certain degree of human subjectivity. Therefore, automated highway evaluation operation also saves an enormous amount of evaluation time and effort while obviating the frequent safety concerns associated with traditional manual evaluation. In the 1970s, many states initiated imaging of highway features using photographic cameras mounted on vans. Later in the 1980s, imaging systems were improved to capture images on videotape or videodisc for subsequent transfer to optical discs that could be viewed at dedicated view stations (Overturf 2001). In the past decade, digital imaging and automated data acquisition systems have become standard equipment for many DOTs and their use has led to further elimination or curtailment of traditional labor-intensive evaluation methods (Dougan, 2001).

A digital imaging system is a combination of optics, interfacing electronics, and software (Figure 1.8). In most cases, digital imaging systems are built of modules from...
different manufacturers allowing different components to interact with each other. Moreover, manufacturers use their own proprietary tools to benchmark their system without following any standard set of techniques and targets and hence provide widely varying evaluations of two similarly performing systems (Reichmann 2003). Therefore, the overall quality of images cannot be determined solely from the manufacturers’ specification of different attributes of image quality such as the dynamic range, signal-to-noise ratio (SNR), spatial resolution, etc. For example, the manufacturer of the DVC 1310C hi-resolution color digital camera with 16.5mm Pentax video lenses (C-mount) used in the FDOT highway evaluation vehicle claims that the equipment has a SNR of 60 dB. However, when installed in the FDOT highway evaluation vehicle, the SNR was determined to be most 50 dB even under well-lit conditions.

Furthermore, emerging developments in the science and art of high-resolution digital imaging also enables precise measurement of attributes of interest, such as distances or heights, directly from image records. In addition, several automated algorithms for pavement surface distress evaluation are being developed and tested (Wang 2000). However, the success of the above automated pavement evaluation techniques eventually depends on the attributes of image quality such as spatial and tonal resolution, and the levels of noise and distortion. Currently, there are no definitive guidelines or standards for evaluating the output from imaging systems. Manufacturers’ specifications of each discrete system components are not reliable in assessing the performance of the assembled imaging system.
Cases have been reported where limited knowledge of modern imaging systems had led to unexpected delays in their implementation (Overturf 2001, Gunaratne et al. 2003). FDOT has developed an automated highway evaluation vehicle in which several problems such as unnatural color quality of forward-view images or too dark pavement images have surfaced with regard to the quality of images (Gunaratne et al. 2003). Many attempts to resolve these problems by trial and error based adjustments have proven to be inefficient with regard to time and cost (Gunaratne et al. 2003). Connecticut Transit (CTTransit) has been seeking to videolog all bus routes incorporating photolog-generated Global Positioning System (GPS) data for their Geographical Information System (GIS) database with the idea of improving the quality of bus route maps and information tools for both CTTransit and its clients. However, the contractor’s lack of familiarity with the new photolog system impeded its full implementation in 1995 (Overturf 2001). On the other hand, quality assurance tests conducted by Pennsylvania DOT on its panoramic imaging program revealed a substantial number of illegible signposts in the collected images (Stoffels, 2003).

2.2 Quality of Images

Figures 2.1 through 2.4 illustrate the variation of digital image quality due to common deficiencies of imaging systems. Image quality can be objectively assessed through physical measurements of the image properties such as color reproduction, tone reproduction, detail reproduction, level of noise, and optical distortion. Specifically designed targets were available to make objective measurements of each of the above
properties in terms of intensity or luminance error, dynamic range, spatial resolution, signal-to-noise ratio, and the degree of distortion, respectively.

Figure 2.1 Forward-View Image – Unclear Traffic Signs as a Result of Low Resolution (640x480)

Figure 2.2 Forward-View Image (resolution of 1300 x 1024) – Undesirable Color Quality Due to Use of Near Infra-red Filter Absorbing Partially Visible Spectrum
2.3 Intensity Measurements

Many of the evaluation procedures discussed in this paper are based on the measurement of intensity values. A black and white digital image (ex: from the pavement camera) contains 8 bits of gray resolution with $2^8$ intensity levels ranging from 0 to 255. Similarly, in a color digital image (from the forward-view camera) any given pixel
contains three intensity values from 0 to 255, for each of the primary colors (red, green, and blue), forming 24 bits (3 x 8) of color resolution. Intensity values encoded into image files through JPG, TIFF, or BMP formats can be measured with imaging programs such as Adobe Photoshop or Adobe Paint Shop Pro. For the present study, the imaging software ImageJ (Rasband 2004) which also allows writing of the scripts in Java for additional processing of parameters such as signal-to-noise ratio, color evaluation, and others was used.

2.4 Evaluation of the Color Reproduction Quality of Digital Images

In some instances, images show unnatural colors (ex: in Figure 2.2) caused by improper settings of white balance, optics, filters, or image software. A Standard Color Checker (Figure 2.5) can be used to compare, measure, and analyze the outputs from different imaging systems in terms of color reproduction under different settings. It is a unique test pattern of 24 scientifically prepared colored squares, designed to help determine the true color balance of the imaging system. Color reproduction is assessed by comparing the color intensity values measured from the image of the Color Checker and its corresponding standard intensity values. The comparison must be made on the same color space with the same chromaticity of the white point. A color space is a model of colors that allows expressing of the color information. There are two types of color spaces:

1. device dependent – same color with particular definitions rendered differently for different devices (i.e., sRGB color space used by digital cameras).

2. device independent – by using a mathematical model, device dependent colors can be converted to device independent colors.
Figure 2.5 Digital Images of a Macbeth Color Checker Taken with the Forward-View Camera with Aperture Settings of F2.8

Figure 2.6 Digital Images of a Macbeth Color Checker Taken with the Forward-View Camera with Aperture Settings of F4.0

Figure 2.7 Digital Images of a Macbeth Color Checker Taken with the Forward-View Camera with Aperture Settings of F5.6

Figure 2.8 Digital Images of a Macbeth Color Checker Taken with the Forward-View Camera with Aperture Settings of F8.0
Most available digital cameras produce images in the sRGB color space with the D65 white point (Lindbloom 2003). However, intensity data for the Macbeth Color Checker used in the present study are in the CIE XYZ colors space with the C white point. Hence, one has to transform the specified color intensity values from device-independent CIE XYZ color space into sRGB color space to be able to use this color checker. This transformation was programmed on the basis of the mathematical procedure described in (Lindbloom 2003).

2.4.1. Selection of Aperture Setting Using Color Evaluation

The setting of appropriate aperture based on color evaluation was illustrated by the following test. The images of the Macbeth Color Checker were obtained by the FDOT highway evaluation vehicle’s forward-view camera at various aperture settings. The camera uses a DVC 1310C with 1296 by 1024 pixel resolution and wide angle Pentax lens with a focal length of 8.5 mm, and saves images as JPG files with a 75% compression ratio. Figures 2.5 – 2.8 show images of Macbeth Color Checker captured at each aperture setting with the appropriate white balance.

The color images can be evaluated for individual intensities of the primary colors or by using luminance as the sole criterion. Luminance (Eqn. (2.1)) represents color or brightness from human perception and provides a single value for comparison as opposed to three separate values for each color channel. Hence, the generally accepted formula for luminance is (Studelle-Schwarz 2004):

\[ Y = 0.3R + 0.59G + 0.11B \]  

(2.1)
where $Y$ is the luminance and $R$, $G$, and $B$ represent intensities of red, green, and blue color respectively in a particular pixel. For example, patch number 15 (red) of the Macbeth Color Checker (Fig. 2.5) imaged under two different apertures (F4.0 and F5.6) can be evaluated as seen in Table 2.1. The device independent values of the patch number 15 provided by the manufacturer in C2 color space are $X_{C2}=20.65$, $Y_{C2}=12.00$, and $Z_{C2}=5.7$. These values were transformed to the sRGB color space (Lindbloom 2003) used by the digital camera as shown in Table 2.1. Table 2.1 also shows the average intensity values of the two images of the red patch of the Color Checker.

<table>
<thead>
<tr>
<th>Channel</th>
<th>Intensity value provided (sRGB)</th>
<th>Measured intensity value (image 1) Aperture 1</th>
<th>Measured intensity value (image 2) Aperture 2</th>
<th>Error image 1</th>
<th>Error image 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>177</td>
<td>187</td>
<td>187</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>G</td>
<td>51</td>
<td>71</td>
<td>56</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>B</td>
<td>61</td>
<td>66</td>
<td>81</td>
<td>5</td>
<td>20</td>
</tr>
<tr>
<td>Average R,G,B Error</td>
<td></td>
<td></td>
<td></td>
<td>11.67</td>
<td>11.67</td>
</tr>
<tr>
<td>Luminance Error</td>
<td></td>
<td></td>
<td></td>
<td>15.35</td>
<td>8.15</td>
</tr>
</tbody>
</table>

The image quality cannot be assessed on the basis of the average error of the three color channels since, as seen in Table 2.1 for both images 1 and 2, the average error could become the same. However, Table 2.1 also shows that the luminance error or the differential form of (Eqn. (2.1)) can be used as the differentiating criterion between images 1 and 2. Based on the luminance criterion, Figure 2.9 shows that the optimum
aperture settings for the tested camera under daylight conditions are between F2.8 and F4.0. In addition, Figure 2.9 also shows the differences in the reproduction of specific colors by the sensor.

Figure 2.9 Luminance Error in the Color Test for Different Apertures

2.4.2. Setting of White Balance Using Color Evaluation

*White balance* refers to the adjustment of the colors in visible light so that white objects would appear white under any given lighting condition. However, white balance depends on the color temperature of the light source and the lighting condition. A white object generates different intensity values for its *Red (R)*, *Green (G)*, and *Blue (B)* color components depending on the color temperature of the light source. The simplest white
balance correction involves “equalization” of the intensity data based on first fixing the green intensity values, and then adjusting the red and blue intensity values using appropriate gain coefficients so that the final $R$, $G$, and $B$ intensities would be equal for an image of a white object. For example, the image of a white board obtained under incandescent light can produce intensity values of $R=200$, $G=250$, and $B=110$. Then, the red and blue gain coefficients that produce white-balancing would be

$$k_R = \frac{250}{200} = 1.25 \quad \text{and} \quad k_B = \frac{250}{110} = 2.27,$$

respectively. Incorrect setting of the white balance can cause a color shift in the image as seen in Figure 2.2. Thus, color evaluation would be vital for evaluating the white balance of a camera under the given lightning conditions, in addition to setting the aperture.

White balance evaluation of the imaging system can also be performed by capturing the image of the MacBeth Color Checker with different white balance settings under different lighting conditions (Figure 2.10 and 2.11). As seen in Figures 2.10 and 2.11, high luminance errors for any channel indicate improper white balance.
Figure 2.10 Intensity Errors for Each Color Channel of the Forward-View Camera (sunlight-based white balance settings)

Figure 2.11 Intensity Errors for Each Color Channel of the Forward-View Camera (incandescent light-based white balance settings)
In addition, color evaluation can also be used to test the efficiency of different filters such as near infra-red or neutral density filters and their performance on the color quality of the imaging system. The Charge Coupled device (CCD) sensors are sensitive in the near infrared (NIR) spectrum and hence longer exposures with CCD cameras usually produce blooming effects in the images. Hence, NIR filters are used to eliminate the near infra-red spectrum (from 700nm-950nm) while maintaining the transmission of intensities across the visible spectrum. These filters are also effective in removing the blooming effect from over-exposed images. The results from the tests on two NIR filters are shown in Figure 2.12 for which images were captured under similar lighting conditions, white balance and aperture (F4.0) settings.

![Figure 2.12 Comparison of Two Different Near Infra-red Filters Mounted on Forward-View Camera](image)

Figure 2.12 Comparison of Two Different Near Infra-red Filters Mounted on Forward-View Camera
Figure 2.12 shows that the response of the NIR filter 2 is superior to that of the NIR filter 1 which was originally used in the camera. As predicted, changing of the filter improved the quality of images obtained from the FDOT imaging vehicle indicating that the originally used NIR filter had partially absorbed the visible spectrum (Figure 2.12). The neutral density filter can be a remedy for situations where it is needed to lower the amount of the light reaching the CCD sensor without affecting the color balance. Therefore, the color evaluation tests also facilitate the selection of appropriate filters.

2.5 Tone Reproduction Quality of Digital Images

Tone reproduction is necessary to ensure that a wide range of light in a real-world scene is conveyed on a display with limited capabilities. Tone reproduction mostly depends on the lighting conditions, and to some extent, on camera settings such as the aperture and software settings such as the gain or exposure. Three attributes that affect the tone reproduction are:

1. the opto-electronic conversion function (OECF) of the camera sensor,
2. flare, and
3. dynamic range.

Flare in an image can be seen in the form of flashes and it is caused by excessive light shining or reflecting directly onto the camera lens. The ISO 12233 target shown in Figure 2.20 can be used with areas of minimal (white) and maximal (black) optical density to measure the flare introduced by an imaging system. When the intensities of resulting black and white (8-bit) images are measured, the intensity value should be 0 and 255, respectively. By measuring the extent of reduction of the original contrast in the
digital image, the influence of flare can be determined (Franziska and James 1999). To minimize flare (Figure 2.13), the imaging system can be fitted with a sunshade that prevents direct impact of sunlight as shown in Figure 2.14. Effects of flare can also be reduced by avoiding imaging operations an hour before sunset and an hour after sunrise.

Figure 2.13 Flare Created by Sunlight Directly Impacting the Optical System

Figure 2.14 Sunshades on Cameras to Prevent Flare
2.5.1. Evaluation of the Dynamic Range

The dynamic range (DR) of a digital imaging system indicates the range of the gray scale (black to white) that the system can differentiate. Hence it is expected that DR would be a fitting indicator of an imaging system and its applicability in accurate image interpretation. DR is measured in units of optical density of (OD) a surface defined as (Dulis 2004):

\[ OD = -\log R \] (2.2)

where \( R \) represents the reflectance of the surface such as that of a standard target.

DR can be determined practically by evaluating the number of gray-level wedges that the given imaging system can recognize in a standard Density Step Target (Figure 2.15). Accomplish this, an image of the target can be captured by the imaging system and the intensity of each gray level wedge measured. Then by visual observation of the corresponding intensity vs. optical density plot (Figure 2.16), the dynamic range of the camera can be determined under the given lighting conditions. In the example shown in Figure 2.16, only the first 11 out of 15 gray wedges are visually distinguishable. Each gray wedge corresponds to a dynamic range of 0.1 and hence the evaluated digital camera is determined to posses a dynamic range of 1.1 with respect to the Density Step Target.
The above target (Figure 2.15) was used to study the variation of the dynamic range of the forward-view camera of the FDOT highway evaluation vehicle at different aperture settings (example in Figure 2.16) and results are shown in Table 2.2. It is seen that the optimum aperture settings for the tested camera under daylight conditions are F4.0 and F5.6 where the dynamic range is maximum. It is noted that during testing, a fixed exposure time was set in the capturing software to control the amount of light striking the camera sensor.
<table>
<thead>
<tr>
<th>Aperture</th>
<th>Dynamic Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1.5</td>
<td>0.7</td>
</tr>
<tr>
<td>F2.0</td>
<td>1.0</td>
</tr>
<tr>
<td>F2.8</td>
<td>1.1</td>
</tr>
<tr>
<td>F4.0</td>
<td>1.5</td>
</tr>
<tr>
<td>F5.6</td>
<td>1.5</td>
</tr>
<tr>
<td>F8.0</td>
<td>0.9</td>
</tr>
</tbody>
</table>

The benchmark values for satisfactory dynamic range are often specified by the user. For example, the Federal Bureau of Investigation (FBI) has defined a criterion in which the dynamic range must cover at least 200 gray levels for an image to be of acceptable quality (FBI 1999) while the National Archives uses in their guidelines a range from 8 to 247 (or 240) gray levels (Franziska and James 1999). These criteria can be converted to dynamic ranges of 0.9 and 1.4, respectively on the optical density scale. During the current research, it was found that for dynamic range, the FBI criterion is sufficient for imaging of highway features as well as pavement distress. Figures 2.17 and 2.18 show the comparison of two images, with an insufficient dynamic range (Figure 2.17) and with a sufficient dynamic range (Figure 2.18), captured by the forward-view imaging system of the FDOT highway evaluation vehicle. Figures 1.34 and 1.35 also show the corresponding intensity or luminance histograms for each image with intensity values plotted along the x-axis and the frequency (i.e., number of pixels found at that intensity) on the y-axis. Most image editing softwares have a built-in capability of producing such a histogram for a given image (Chastain 2004).
2.5.2. Evaluation of Proper Exposure Settings

The gray scale range of an image captured by an imaging system can also reveal whether the exposure of the camera has been properly set. The following characteristics must be checked in the intensity or luminance histogram:

(1) To ensure smooth transition between the tones, there should be an even distribution of intensities (or tones) through the entire range of tones with no sharp rises or drops (Arrow 1 in Figure 2.18),

(2) To ensure that the image is not under-exposed, there should not be a significant amount of low intensities in the image (Figure 2.17), and

(3) To ensure that the image is not over-exposed with consequent loss of information, there should be gaps in the low and high intensity areas (Arrows 2 in Figure 2.18).

Figure 2.17 Insufficient Gray Scale Range of Forward-View Image with Corresponding Luminance Histogram Plots
If any of the above conditions are not met, the exposure settings on the camera must be changed and the test repeated.

2.6 Detail Reproduction Quality of a Digital Image

2.6.1 Theoretical Limits of Spatial Resolution

Image resolution is a significant attribute of imaging systems because it ensures retention of information relating to highway features. Moreover, higher image resolution permits more accurate estimates of dimensions such as distances between features of interest or crack widths that are to be made from the images. The resolution of an imaging system is influenced not only by the sensor sensitivity but also by the optical settings. Therefore, evaluation of image resolution can also ensure that the imaging system is in proper focus.
The magnification, $M$, (ratio of image height $H_I$ to object height $H_0$) of an object at a distance $O$ from an imaging system with focal length, $f$, can be computed using the lens equation as (Edmund Industrial Optics 2003):

$$M = \frac{H_I}{H_0} = \frac{f}{f + O}$$

(2.3)

Every camera has its system limitations and when the frequency of information flow exceeds the frequency at which a pixel can register, the phenomenon of aliasing occurs. The highest frequency that the CCD sensor can record is called the Nyquist frequency ($N_f$) which can be determined as $1/(2p)$ where $p$ is the pixel pitch. For example, for the DVC1310C digital camera used in FDOT highway evaluation vehicle with a pixel pitch of 6.7 µm, the Nyquist frequency is 74.6 cycles/mm or 74.6 line pairs (lp)/mm.

Therefore, for any object feature in image to clearly appear on the sensor, the required minimum height of its image, $H_I$, must be theoretically equal to the sensor’s pixel pitch $p$. Then, if the height of the object feature (such as text on traffic and safety signs or crack widths), $H_0$, is known, one can obtain the focal length required for clear recognition of the image of that feature by substituting $H_I = p$ in Eqn (2.3):

$$f = \frac{pO}{H_0 - p}$$

(2.4)

Therefore, for given $f$ and $O$, using Eqn. (2.4) the theoretical minimum height of an object feature ($H_0$) can be determined as:
In Section 4.2 the above criterion will be compared to an alternative criterion based on practical evaluation of the spatial resolution.

One can also compute the effect of the exposure time and vehicle speed on the sharpness of an image. If the change in the image size on the sensor within the exposure time is more than half of the pixel pitch, blurred images can occur. From Eqn. (2.3) one can express the height of the image of an object on the sensor of a moving vehicle at a given instant \( H_t \). If the exposure time is \( T_e \) and the vehicle speed is \( V \), the change in size of the image on the sensor within the exposure time can be obtained from Eqn. (2.3) as:

\[
\Delta H = T_e \frac{dH}{dt} = T_e \left( \frac{dH_0}{dt} \frac{dO}{dO} \right) = -T_e \frac{H_0 f}{(f + O)^2} V
\]

Table 2.3 shows the maximum possible change in the size of an image on the sensors of the FDOT vehicle’s optical systems, computed based on a 279.4 mm (11 inch) tall highway sign \( H_0 \).

\[
H_0 = \frac{p(f + O)}{f}
\]
Table 2.3 Change in the Image Size (in pixels) Due to Vehicle Movement

<table>
<thead>
<tr>
<th>ΔH [number of pixels]</th>
<th>Exposure, T_E [ms]</th>
<th>40 (1/25)</th>
<th>10 (1/100)</th>
<th>4 (1/250)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Forward-View</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(f = 8.5 mm)</td>
<td>8.94 (20 mph)</td>
<td>0.13</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>(O=30.48m)</td>
<td>22.35 (50 mph)</td>
<td>0.34</td>
<td>0.07</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>31.29 (70 mph)</td>
<td>0.48</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td><strong>Side-View</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(f = 20 mm)</td>
<td>8.94 (20 mph)</td>
<td>1.3</td>
<td>0.31</td>
<td>0.13</td>
</tr>
<tr>
<td>(O = 15.24m)</td>
<td>22.35 (50 mph)</td>
<td>3.2</td>
<td>0.81</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>31.29 (70 mph)</td>
<td>4.5</td>
<td>1.1</td>
<td>0.45</td>
</tr>
</tbody>
</table>

According to Table 2.3, exposure times of 40 milliseconds affect the side-view camera for speeds higher than 20 mph since the change exceeds more than half a pixel. Furthermore, it can be seen that exposure times of 10 milliseconds or lower do not affect the quality of images for any speed up to 70 mph.

2.6.2. Modulation Transfer Function (MTF) Approach for Determining Spatial Resolution

In the past, the resolving power of an imaging system, or its ability to separate two lines was measured in line pairs per millimeter based on the USAF 1951 lens test chart. Because human perception and judgment were involved in determining the highest resolution pattern where detail was still visible, benefits of repeatability could not be assured using this method. This problem has been resolved now with the introduction of the Modulation Transfer Function (MTF). MTF is a measure of the contrast transmission capability of an imaging system at a given spatial frequency (ω), typically measured in line pairs per millimeter (lp/mm). MTF of an imaging system can be defined as the ratio...
of the modulation of the image of a standard sinusoidal (bar pattern) target captured by
that imaging system, $M_i$, to that of the target itself, $M_o$ (Nill 2001):

$$MTF = \frac{M_i}{M_o}$$ (2.7)

Therefore, it is necessary to first determine the modulation values for each area of the
target. The transmittance of a sinusoidal area of this target $T_{\sin}(x)$ can be described by the
equation:

$$T_{\sin}(x) = t_0 + t_1 \cos 2\pi \omega x + t_2 \cos 4\pi \omega x + t_3 \cos 6\pi \omega x + ...$$ (2.8)

where $t_i$ is the amplitude of the fundamental frequency and $t_2, t_3, etc$ are the amplitudes of
the harmonics, and $\omega$ is the spatial frequency, which can be in terms of cycles per mm.

MTF is defined as frequency amplitude response or modulus of the Fourier
transform of the line spread function (Dallas 2004). According to Fourier theory, if $T_{\sin}(x)$
is a periodic function, then it can also be written as follows (Lamberts 2004):

$$T_{\sin}(x) = \frac{1}{2} a_0 + \sum_{n=1}^{\infty} \left[ a_n \cos 2\pi n \omega x + b_n \sin 2\pi n \omega x \right]$$ (2.9)

where:

$$a_n = 2\omega \int_{-1/2\omega}^{1/2\omega} T_{\sin}(x) \cos 2\pi n \omega x (dx) \quad (n = 0, 1, 2, 3 \ldots \infty)$$ (2.10)
\[ b_n = 2\omega \int_{-1/2\omega}^{1/2\omega} T_{\sin}(x) \sin 2\pi nx \, dx \quad (n = 0, 1, 2, 3 \ldots \infty) \] (2.11)

Equation 2.8 includes terms up to infinity but with most test patterns the magnitude of harmonics beyond \( n = 3 \) is negligible. In most cases, starting point of the cosine function is arbitrary resulting in phase angle \( \phi \) that has to be taken into account (Figure 2.19).

![Figure 2.19 Arbitrary Position of the Starting Point](image)

Then by using trigonometric identity \( \cos(x - y) = \cos x \cos y + \sin x \sin y \), Eqn. (2.9) can be rewritten as:

\[ T_{\sin}(x) = \frac{1}{2} a_0 + \sum_{n=1}^{\infty} [c_n \cos(2\pi nx - \phi_n)] \] (2.12)

where:

\[ a_n = c_n \cos \phi_n \] (2.13)
\[ b_n = c_n \sin \phi_n \]  
(2.14)

\[ \phi_n = \arctan \left( \frac{b_n}{a_n} \right) \]  
(2.15)

\[ c_n = \pm (a_n^2 + b_n^2)^{1/2} \]  
(2.16)

Then based on Eqn. (2.12), one can determine maximal and minimal transmittance as:

\[ T_{\text{max}} = a_0 + c_1 + c_2 + c_3 + \ldots \quad \text{(if } x = 0 \text{ and } \phi = 0) \]  
(2.17)

\[ T_{\text{min}} = a_0 - c_1 + c_2 - c_3 + \ldots \quad \text{(if } x = \frac{1}{\omega} \text{ and } \phi = 0) \]  
(2.18)

Based on Equations (2.17) and (2.18), the peek to peek modulation can be determined as:

\[ M_0 = \frac{T_{\text{max}} - T_{\text{min}}}{T_{\text{max}} + T_{\text{min}}} = \frac{(c_1 + c_3 + \ldots)}{(a_0 + c_2 + \ldots)} \]  
(2.19)

For reflecting targets, \( M_0 \) can be defined as (Nill 2001):

\[ M_0 = \frac{R_{\text{max}} - R_{\text{min}}}{R_{\text{max}} + R_{\text{min}}} \]  
(2.20)

where \( R_{\text{min}} \) and \( R_{\text{max}} \) are the minimum and maximum reflectances of the bar pattern of a given spatial frequency of the target viewed at a given a uniformly illuminated background. \( M_0 \) can also be expressed in terms of the corresponding optical densities (Eqn. 2.2) as:
\[ M_0 = \frac{10^{-D_{\text{min}}} - 10^{-D_{\text{max}}}}{10^{-D_{\text{min}}} + 10^{-D_{\text{max}}}} \]  

(2.21)

where \( D_{\text{min}} \) and \( D_{\text{max}} \) represent the minimum and maximum density values, respectively. Hence, \( M_0 \) can be evaluated by a photoelectric or densitometer scanner with its gain calibrated to directly measure optical densities of the bar pattern target.

On the other hand, the modulation of the image can be determined as (Nill 2001):

\[ M_i = \frac{(I_{\text{max}} - I_{\text{min}})}{(I_{\text{max}} + I_{\text{min}})} \]  

(2.22)

where, \( I_{\text{max}} \) and \( I_{\text{min}} \) are the maximum and the minimum intensity values of the image of the sinusoidal bar pattern corresponding to the desired spatial frequency.

To obtain \( M_i \), intensity values are measured on the basis of electrical pulses generated on the sensor and inverted to actual intensity values using the Opto-electronic Conversion Function (OECF) of the camera sensor. OECF defines the relationship between input luminance and the grayscale or digital intensity output from the camera. The OECF of a camera can be measured by using a test chart with known gray levels of its patches and the method described in ISO 14524 (McDowell 1999) or algorithm described in (Hasler and Susstrunk 2002).

2.6.3. **Contrast Transfer Function (CTF)**

The contrast transfer function (CTF) of an imaging system is its relative contrast response to a square wave modulation. It is determined from the detector response to a target containing a series of black and white resolution bars with 100 percent contrast and
increasing in spatial frequency (Figure 2.20). An approximate expression for determining
CTF solely from the image of the target can be determined as (Koren 2003):

$$CTF = \frac{C(\omega)}{C(0)} \times 100\%$$  \hspace{1cm} (2.23)

where $C(\omega)$ is the contrast at the spatial frequency of $\omega$ equal to:

$$C(\omega) = \frac{(I_w - I_B)}{(I_w + I_B)}$$  \hspace{1cm} (2.24)

and $C(0)$ is the low frequency (black-white bars) contrast computed as:

$$C(0) = \frac{(I_{\text{max}} - I_{\text{min}})}{(I_{\text{max}} + I_{\text{min}})}$$  \hspace{1cm} (2.25)

where $I_B$ is the average intensity of black areas $I_1, I_2, I_3, \ldots, I_9$ at a given frequency ($AB$
 in Figure 2.21) $I_W$ is the average intensity of white areas $I_{11}, I_{12}, I_{13}, \ldots, I_{18}$ at the given
frequency $I_{\text{max}}$ and $I_{\text{min}}$ are the positive and negative peak intensities for the bar pattern at
the given frequency.

The intensity profile plot for a scale number ($SN$) of 8 on ISO12233 target is
shown in Figure 2.21. It is noted in the inset that the points A and B lie on the white and
black areas, respectively, of the target. The corresponding spatial frequency on the sensor
can be computed from $SN$ using the generic equation of the target as:
\[ \omega = \frac{50SN}{PH} = \frac{50(8)}{6.9 \, mm} = 58 \, lp/mm \]

where \( SN \) is the scale number on the ISO 12233 target and \( PH \) represents the picture height on the sensor.

Figure 2.20 ISO 12233 Resolution Chart (inset is shown for the horizontal resolution bar 8)

Figure 2.21 Intensity Profile Plot for the Image of an ISO12233 Target for Scale Value of 8 (Figure 2.20) Corresponding to a Spatial Frequency of 58 lp/mm
A series expansion can convert the square wave CTF to its equivalent sine wave MTF, as (Nill 2001):

\[
MTF(\omega) = \frac{\pi}{4} \left[ CTF(\omega) + \frac{CTF(3\omega)}{3} - \frac{CTF(5\omega)}{5} + \frac{CTF(7\omega)}{7} + \frac{CTF(11\omega)}{11} - \ldots \right]
\]  \hspace{1cm} (2.26)

The number of CTF modulation terms in Eqn. (2.26) depends on the cut-off frequency \(\omega_c\) at which MTF equals 0%. For \(\omega > \frac{\omega_c}{3}\) and \(C(\omega) < 0.7C(0)\), Eqn. (2.26) can be approximated by:

\[
MTF(\omega) = \frac{\pi}{4} CTF(\omega)
\]  \hspace{1cm} (2.27)

Therefore, for the visual resolution bars of the ISO 12233 resolution chart corresponding to a spatial frequency of 58 lp/mm (Figure 2.21), the MTF value can be computed as:

\[
MTF(58) = \frac{\pi}{4} \frac{C(58)}{C(0)} = 0.785 \left[ \frac{(130.5 - 56.2)}{(130.5 + 56.2)} \right] \frac{100\%}{155.5 - 13.4} = 37\%.
\]

Figure 2.22 shows the results of the resolution test for the forward-view camera of the FDOT highway evaluation vehicle. If one determines a MTF value of 10% as the minimum allowable based on Rayleigh diffraction limit MTF of 9%, then the horizontal resolution of the above camera is seen to be 42 lp/mm while its vertical resolution is 78 lp/mm. A MTF plot can also be used to evaluate the relative resolution powers of different digital cameras. As seen in Figure 2.23, for a MTF value of 10%, the vertical
resolution of the mega-pixel camera used in the FDOT vehicle’s forward-view imaging system (75 lp/mm) is almost double that of the VGA camera (42 lp/mm).

Figure 2.22 MTF Response of the Forward-View Digital Camera (1296x1024)

Figure 2.23 Comparison of MTF Response of Mega-pixel (1296x1024) and VGA (640x480) Resolution Cameras
The spatial resolution values plotted in a MTF plot are applicable to the sensor. In order to verify if a given imaging system is capable of legibly registering information from a target object, the sensor resolution has to be transformed to spatial resolution at the desired distance in the field of view using Eqn. (2.3). Then, if, \( H_1 = \frac{1}{2 \omega_{MTF(10\%)}} \)
the minimum recognizable height of a feature, \( H_0 \), can be determined in terms of the distance, \( O \), as:
\[
H_0 = \frac{f + O}{2 \omega_{MTF(10\%)}, f}
\]  

(2.28)

Similarly, based on evaluation of spatial resolution of the imaging system, the minimum recognizable crack width can be determined from a captured image (Figure 2.24). For example, the pavement imaging system of the FDOT highway evaluation vehicle employs Basler L103 line-scan digital camera and Sigma Fisheye optics with a focal length of 15 mm. The pixel pitch of the sensor, \( p \), is 10 µm and its distance from the pavement is 9.25 ft. Hence, the Nyquist frequency of this imaging system is \( 1/2p \) or 50 lp/mm However, the spatial resolution testing of this camera revealed that MTF(10%) corresponds to a spatial frequency of 28 lp/mm indicating that the minimum recognizable crack width is 3.37 mm (0.13 inch) (Sokolic et al. 2004) (Figure 2.5). It is seen that Eqns. (2.5) and (2.28) furnish two distinct criteria for minimum recognizable feature based on the theoretical Nyquist frequency and the evaluated MTF, respectively.
Table 2.4 Sample Guidelines for Setting Focusing Distances (in meters) of the Forward-View and Side-View Cameras (with a pixel pitch of 6.7 µm and MTF10 = 74 lp/mm)

<table>
<thead>
<tr>
<th>Focal Length \ Height of the roadway sign text</th>
<th>6.0mm</th>
<th>8.5mm</th>
<th>12.0mm</th>
<th>20.0mm</th>
<th>25.0mm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ny.</td>
<td>MTF10</td>
<td>Ny.</td>
<td>MTF10</td>
<td>Ny.</td>
</tr>
<tr>
<td>1 cm</td>
<td>8.9</td>
<td>8.9</td>
<td>12.7</td>
<td>12.6</td>
<td>17.9</td>
</tr>
<tr>
<td>2 cm</td>
<td>17.9</td>
<td>17.8</td>
<td>25.4</td>
<td>25.2</td>
<td>35.8</td>
</tr>
<tr>
<td>5 cm</td>
<td>44.8</td>
<td>44.4</td>
<td>63.4</td>
<td>62.9</td>
<td>89.5</td>
</tr>
<tr>
<td>10 cm</td>
<td>89.5</td>
<td>88.8</td>
<td>126.9</td>
<td>125.8</td>
<td>179.1</td>
</tr>
<tr>
<td>20 cm</td>
<td>179.1</td>
<td>177.6</td>
<td>253.7</td>
<td>251.6</td>
<td>358.2</td>
</tr>
<tr>
<td>30 cm</td>
<td>268.7</td>
<td>266.6</td>
<td>380.6</td>
<td>377.4</td>
<td>537.3</td>
</tr>
<tr>
<td>50 cm</td>
<td>447.8</td>
<td>44.0</td>
<td>634.3</td>
<td>629.0</td>
<td>895.5</td>
</tr>
</tbody>
</table>

Table 2.5 Sample Guidelines for Setting Focusing Distances (in meters) of the Pavement Camera (with a pixel pitch of 10.0 µm and MTF10 = 28 lp/mm)

<table>
<thead>
<tr>
<th>Focal Length \ Crack width</th>
<th>4.7 mm</th>
<th>6.0 mm</th>
<th>8.5 mm</th>
<th>15.0 mm</th>
<th>20.0 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ny.</td>
<td>MTF10</td>
<td>Ny.</td>
<td>MTF10</td>
<td>Ny.</td>
</tr>
<tr>
<td>1 mm</td>
<td>0.5</td>
<td>0.3</td>
<td>0.6</td>
<td>0.3</td>
<td>0.8</td>
</tr>
<tr>
<td>2 mm</td>
<td>0.9</td>
<td>0.5</td>
<td>1.2</td>
<td>0.7</td>
<td>1.7</td>
</tr>
<tr>
<td>3 mm</td>
<td>1.4</td>
<td>0.8</td>
<td>1.8</td>
<td>1.0</td>
<td>2.5</td>
</tr>
<tr>
<td>4 mm</td>
<td>1.9</td>
<td>1.0</td>
<td>2.4</td>
<td>1.3</td>
<td>3.4</td>
</tr>
<tr>
<td>5 mm</td>
<td>2.3</td>
<td>1.3</td>
<td>3.0</td>
<td>1.7</td>
<td>4.2</td>
</tr>
</tbody>
</table>
Tables 2.4 and 2.5 were developed based on Eqn. (2.5) (Nyquist frequency criterion) and Eqn. (2.28) (MTF criterion) to illustrate the determination of the focusing distances to objects that need to be clearly captured by an optical system for specific focal lengths. It was assumed that the sensor has pixel pitch of 6.7 µm.

2.7 Level of Noise

2.7.1. Definition

Unrelated energy fluctuations in the optical signal are referred to as noise which can occur during image capture, transmission, or processing, depending on the contents of the image. Noise has a significant impact on the quality of images and hence evaluation and subsequent control of noise can certainly improve the quality of images. The primary sources of noise that originate from the imaging system are:

(1) optical imperfections,

(2) amplifier noise,

(3) fixed pattern noise,

(4) color shift noise,

(5) compression artifacts noise, and

(6) temporary varying noise, which is random noise due to photon noise, dark noise, and read noise of the sensor.
The causes of the above sources of noise are described in detail in (Roper Scientific 2003) and (Askey 2003). The compression artifact noise can be minimized by performing an appropriate compression set up on the capturing software. Through visual testing of uncompressed images captured by forward-view and side-view imaging systems of the FDOT highway evaluation vehicle, it was determined that images captured with an 80% JPEG compression show minimal pixelization and distortion (Gunaratne et al. 2003).

On the other hand, noise becomes a significant factor when optical systems with relatively long focal length are used in a moving vehicle, especially under low-lighting conditions and low shutter speeds. Furthermore, vehicle vibration caused by road roughness also causes vibration noise. Figure 2.25 shows two images taken by the side-view camera under static (engine idling) and vibratory conditions (engine speed of 3,000 rpm) where a slight blur is seen to occur due to the vehicle’s vibration.

![Figure 2.25 Images Taken with the Side-View Camera of FDOT Highway Evaluation Vehicle in Static and Vibratory Modes](image)

The FDOT highway evaluation vehicle’s vibration effect was quantified by attaching a laser pointer to the forward-view camera enclosure. In order to quantify the effects of vibration, the laser beam was traced on a white board 8 meters away from the
camera for different engine speeds from idle up to 4,000 rpm (example shown in Figure 2.26 is for engine speed of 3,000 rpm).

The maximum vertical angular deviation of the laser beam due to vehicular vibration is given by:

\[ \Delta = \frac{(CA)}{Distance} \]  

(2.29)

Based on the above angular deviation, the maximum vertical position change (on the sensor) of the image of an object at a distance \( O \) due to the vibration effect can be determined as (Eqn. (2.5)):

\[ \Delta_{\text{vibration}} = \frac{f}{(f + O) Distance \ (\text{pixel pitch})}[\text{pixels}] \]  

(2.30)
Table 2.6 shows the magnitude of $\Delta_{\text{vibration}}$ for the imaging systems tested in this work. Based on the results, one would expect a more pronounced effect of vibration on the side-view camera. It was also seen that the effect of the vibration on image quality can be minimized by using a special rubber shock-absorption casing for the camera. However, if distance measurements are to be performed based on the images, the effect of vehicular vibration needs to be account for.

<table>
<thead>
<tr>
<th>Camera</th>
<th>Given Values</th>
<th>Horizontal Displacement [number of pixels]</th>
<th>Vertical Displacement [number of pixels]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forward-View</td>
<td>$f = 8.5 \text{ mm}$</td>
<td>0.6</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td>$O = 30.48 \text{ m (100 ft)}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Side-View</td>
<td>$f = 25 \text{ mm}$</td>
<td>1.9</td>
<td>3.3</td>
</tr>
<tr>
<td></td>
<td>$O = 15.24 \text{ m (50 ft)}$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.7.2. Evaluation of Noise through Measurements of Signal-to-Noise Ratio

Signal-to-noise ratio (SNR) describes the relative magnitude of a signal compared to the noise or uncertainty in that signal. Hence SNR is also considered as an important parameter in the assessment of image quality (Table 2.7).

<table>
<thead>
<tr>
<th>SNR (dB)</th>
<th>Image Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>More than 30</td>
<td>Excellent, no perceptible noise.</td>
</tr>
<tr>
<td>25</td>
<td>Good, only little noise.</td>
</tr>
<tr>
<td>20</td>
<td>Average, noise visible as fine granulation.</td>
</tr>
<tr>
<td>15</td>
<td>Bad, intensive noise, information drowns.</td>
</tr>
<tr>
<td>Less than 10</td>
<td>Unusable.</td>
</tr>
</tbody>
</table>
Although there are several methods of measuring SNR (Hasler and Susstrunk 2002), SNR was determined in this work by measuring the luminance (Eqn. (2.1)) from at least 1,000 randomly chosen sub-areas in the image. In order to perform this evaluation, Munsell N9-white matte and Munsell N3-black matte boards (or black and white patches on the Standard Color Checker shown in Figure 2.5) were imaged. Under these conditions, black and white SNR can be defined separately as (Young et al. 1998):

\[
SNR_{\text{black}} = 20 \log_{10} \left( \frac{\mu_{\text{white}} - \mu_{\text{black}}}{\sigma_{\text{black}}} \right) \text{dB} \quad (2.31)
\]

\[
SNR_{\text{white}} = 20 \log_{10} \left( \frac{\mu_{\text{white}} - \mu_{\text{black}}}{\sigma_{\text{white}}} \right) \text{dB} \quad (2.32)
\]

where \((\mu_{\text{white}}, \sigma_{\text{white}})\) and \((\mu_{\text{black}}, \sigma_{\text{black}})\) represent the averages and the standard deviations of the pixel intensities of the black and white patches of the image of Macbeth Color Checker (Figure 2.5). Eqns. (2.31) and (2.32) were used to evaluate the SNR at six different aperture settings under sunny conditions. This was facilitated by ImageJ image processing software that computes the standard deviations and average values of pixel intensities for regions of interest (Figure 2.27). From the results of similar tests, users of imaging systems would be able to determine the optimum aperture settings and lighting conditions that would minimize the noise.
Figure 2.27 Measurement of Average White and Black Intensity Values and Standard Deviations of the Image of Macbeth Color Checker for an Aperture Setting of F5.6

As seen in Table 2.8, the most desirable $SNR_{white}$ and $SNR_{black}$ (about 50 dB) are obtained for an aperture setting of F4.0. For the DVC1310C camera used in this test, the manufacturer specified SNR is 60 dB for 10-bit images. Because of the transformation from a 10-bit to an 8-bit (JPG) image, a lower SNR (ex: 50 dB) can naturally be expected. However, any further lowering of SNR (Table 2.8) due to aperture settings or lighting condition variations can be attributed to the previously mentioned sources of noise. This further underscores the need for independent user-driven evaluation of imaging systems. These criteria also enable the user to determine the most favorable lighting conditions. For example, the optimal white and black SNR values for the forward camera at an aperture setting of F4.0 in cloudy conditions were found to be 39.3 and 40.5 dB, respectively.
Table 2.8 Results of the SNR Testing for Forward-View Camera at Various Aperture Settings (sunny conditions)

<table>
<thead>
<tr>
<th>Aperture</th>
<th>AVE_{white}</th>
<th>AVE_{black}</th>
<th>StDEV_{white}</th>
<th>StDEV_{black}</th>
<th>SNR_{white} [dB]</th>
<th>SNR_{black} [dB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1.5</td>
<td>236.5</td>
<td>101.7</td>
<td>0.936</td>
<td>1.995</td>
<td>43.2</td>
<td>36.6</td>
</tr>
<tr>
<td>F2.0</td>
<td>232.0</td>
<td>77.1</td>
<td>1.147</td>
<td>0.885</td>
<td>42.6</td>
<td>44.8</td>
</tr>
<tr>
<td>F2.8</td>
<td>229.5</td>
<td>64.9</td>
<td>0.685</td>
<td>1.300</td>
<td>47.6</td>
<td>42.0</td>
</tr>
<tr>
<td>F4.0</td>
<td>239.4</td>
<td>48.3</td>
<td>0.592</td>
<td>0.548</td>
<td>50.2</td>
<td>50.8</td>
</tr>
<tr>
<td>F5.6</td>
<td>185.4</td>
<td>28.1</td>
<td>1.522</td>
<td>0.444</td>
<td>40.3</td>
<td>51.0</td>
</tr>
<tr>
<td>F8.0</td>
<td>67.2</td>
<td>5.7</td>
<td>1.141</td>
<td>0.887</td>
<td>34.6</td>
<td>36.8</td>
</tr>
</tbody>
</table>

2.7.3. Effect of the Noise on Dynamic Range

If images are used in automatic detection of features and evaluation of pavement distress in particular, the maximum tolerable noise level that will allow a specific algorithm to detect a specified difference in grayscale (ex: 5%) becomes a key issue. At a certain level of noise, the detection algorithm fails to recognize and distinguish the required features (such as pavement cracks) from their background.

In general, thresholds of recognition of one noise level from another can be expressed in terms of a signal-to-noise ratio. If one considers images where the pixels at levels 1 and 2 have average intensity values of $\mu_1$ and $\mu_2$, then based on Eqn. (2.31) or (2.32) the recognition threshold for level 1, $k_{level1}$, can be defined as:

$$k_{level1} = 20\log_{10} \left[ \frac{\mu_2 - \mu_1}{\sigma_1} \right] dB$$

(2.33)

Assuming that the camera captures a 10-bit grayscale image with 1024 ($2^{10}$) gray levels. After capture, the image is transformed into an 8-bit BMP file with only 256 ($2^{8}$) different gray levels where 5% of the gray scale represents approximately 13 ($256 \times 5\%$)
gray levels (ex: levels 1 and 2 in Figure 2.28 (a) with intensities of 13 and 26 respectively). Figure 2.28 (b) and 2.28 (c) show two images of a crack with the noise represented by the standard deviations of the intensity of 3.7 and 10.7 respectively. Based on Eqn. (2.33), $k_{level}$ values for the images in Figs. 2.28 (b) and 2.28 (c) are 11 dB and 1.7 dB, respectively. Then, judging from the criteria in Table 2.7, it can be realized why automatic detection of the crack in Figure 2.28 (c) is practically impossible. Hence Eqn. (2.33) and Table 2.7 provides an excellent set of tools to assess the limitations of a pavement imaging system in advance of automatic distress (crack) detection.

Figure 2.28 (a) Maximum Tolerable Noise Within Gray Levels; (b) Example of Low Level of Noise; and (c) Example of High Level of Noise Prohibiting Cracks Recognition
2.8 Optical Distortion

Although imaging technology has progressed to the point where it is now possible to correct many lens defects and color shifts, most digital cameras still suffer from lens distortion. Lens distortion is caused by lenses of relatively inferior quality in which the magnification varies from the center of the lens to the edges. In fixed focal length lenses, the effect is less prominent than in zoom lenses. In general photography, distortion may hardly be noticeable. However, when parts of the image are subjects composed of straight edges, such as buildings or right-of-way highway features, barrel or pincushion distortion may affect the quality of the image (Figure 2.29). Moreover, if the images are used for evaluations such as distance gauging between certain image features, then a correction must be made for the level of distortion.

![Figure 2.29 Images Affected by Barrel and Pincushion Lens Distortions](image)

One method of measuring distortion is based on capturing the image of a specially printed target, such as Edmund Optics 5%, 10%, and 15% distortion targets, at radial heights between 20mm and 80mm. When a curved line of a specific distortion target (i.e., 10% as shown in Fig. 2.30) at a given radial distance appears straight, that specific
distortion (i.e., 10%) can be considered as the distortion in the image at the given radial distance appears straight, that specific distortion (i.e., 10%) can be considered as the distortion in the image at the given radial distance. It was found that the forward-view camera with a wide angle lens of focal length 8.5 mm used in this illustration suffers from a 10% barrel distortion at a radial distance of 60 mm.

Figure 2.30 10% Barrel Distortion of the Forward-View Camera Lens in the FDOT Highway Evaluation Vehicle

A more objective method of measuring the image distortion is to capture an image of a uniform grid (Figure 2.31). When the distance between two given points on the target and the distance between the corresponding points on the image are measured separately, the distortion can be determined. For example, Figure 2.31 shows a standard grid and its image captured by the forward-view camera of the FDOT highway evaluation vehicle at a distance of 1 m away from the grid target. The standard length of the line $AB$ segment is 50 mm. By using the program *ImageJ* (Rasband 2004), 69 pixels can be counted on $A'B'$, which is the image of $AB$. This represents a distance of 462 μm (69 x 6.7 μm) on the sensor. If the camera produces no distortion, Eqn. (2.3) can be used, with a
focal length of 8.5 mm and a target distance of 1 m, to determine the ideal size of the image of AB as 425 µm. Hence the barrel distortion of this camera can be computed as \((462-425)/4.25\) or 8.7% for the given radial distance.

![Figure 2.31 Evaluation of Lens Distortion Based on Comparison of Object and Image Lengths](image)

2.9 Guidelines for Maximizing the Efficiency of Imaging Operations

The following steps were found to help to maximize the efficiency of the imaging operations:

(1) measure the dynamic range and gray-scale range of the imaging system for different aperture settings. Determine the aperture, exposure setting, and gain combination (if the latter option is available in the software) that provides satisfactory dynamic range and gray-scale range responses under typical lighting conditions,

(2) evaluate the Signal-to-Noise ratio and determine the aperture, exposure, and gain setting combination (if available in software) required to minimize the noise in images under typical lighting conditions. Then the user can determine the
optimum aperture, exposure, and gain combination that satisfies both the color reproduction and noise criteria. The image compression ratio that would minimize the compression artifacts noise can also be determined,

(3) assess the color reproduction capability of the imaging system by using a Standard Color Checker. The optimum lighting conditions as well as the corresponding white balance can be determined using the described procedure,

(4) evaluate the spatial resolution of the imaging system with respect to highway/pavement feature identification needs by deriving the Modulation Transfer Function of the system using a spatial resolution target. Criteria provided in this article will also enable setup of the field of view and positions of the imaging systems, and

(5) check the degree of distortion in the images using the presented methodology. By estimating the level of image distortion, the estimates of crack widths and distances between desired features can be refined. Moreover, the same criteria can be used to select appropriate optics that minimizes the level of distortion.
CHAPTER 3

INVESTIGATION OF NOISE AFFECTING PAVEMENT DISTRESS IMAGES
AND ENHANCEMENT OF IMAGES USING NOISE FILTRATION

3.1 Noise that Affect CCD Sensors

Noise that degrades the quality of digital images can be described as the visible effects of a cumulative electronic error or other interferences or compression artifacts that appear in the final image obtained from a digital camera. Images acquired using modern CCD sensors (Figure 3.1) can become contaminated by random noise originating from a variety of sources such as variations in the detector sensitivity, environmental variations, the discrete nature of radiation, transmission or quantization errors, etc (Figure 3.9).

Noise, which is not an inherent part of the signal, arises as a result of unmodelable processes persistent in the production and capture of a signal. Therefore, noise reflects how well the sensor and the digital signal processing systems function inside the camera.

Figure 3.1 Typical CCD Sensor Containing Micro-lenses, Colored Filters, and Photosensitive Diodes (Source: Fuji Photo Film USA)
Noise can be described through the variation in the pixel intensities of a digital image of a uniformly bright area. Noise is usually described by its probabilistic characteristics. Idealized noise, also called white noise, is a signal with a power spectrum (energy per unit time) falling within given frequency bins homogeneously distributed across all frequencies. Having power at all frequencies, the total power of such a signal would be infinite and therefore the white noise signal is purely a theoretical concept. By considering noise of a certain signal as white noise in the frequency domain one can define important statistical properties of that noise in time. As an example, if a random process $w[n]$ is white noise, its values $w[n]$ and $w[m]$ are uncorrelated for every $n$ and $m$ where $m \neq n$:

$$E(w[n]w[m]) = 0 \quad (3.1)$$

A close approximation to noise that occurs in many practical cases related digital cameras is Gaussian noise (Sonka et al. 1999). Gaussian noise, a special case of white noise, is a random noise with a normal probability distribution (Figure 3.2). The Gaussian noise will be considered as additive noise with a Gaussian distribution.

![Figure 3.2 Gaussian Probability Density Function](image-url)
In order to comprehend the mechanisms that introduce noise to CCD sensors, one must possess a thorough understanding of the structure of CCD sensors. Hence the following chapters describe the important aspect of the composition of CCD sensors.

3.1.1. Overview of Charge-Coupled Device (CCD)

The heart of the digital imaging system is the CCD sensor that relies on the physical conversion of the light, or photons, to an electronic charge. The charge is generated by electrons excited from the poly-silicon valence band to the silicon dioxide conduction band (Figure 3.3) due to a reaction between the silicon and the impeding light (Davies and Fennessy 2001). The charge will be stored as a potential in the silicon substrate layer located directly under the sensor. Therefore the number of electrons created for a given wavelength of light will be a linear function of the number of photons per unit time and unit area.

![Figure 3.3. The CCD Sensor – Detail (Davies and Fennessy 2001)](image)
The CCD sensor is created by using a technique allowing the assembly of thousands or millions of separate elements, or pixels, together. Generally, the greater number or pixels, the greater the detail that can be achieved in the resulting image. The current market favors the full frame CCD and the interline CCD that differ in both quality and cost. The pavement imaging system of the FDOT highway evaluation vehicle contains Basler L-103 camera with a line-scan CCD sensor shown in Figure 3.4 (a) with linear array of 2048 pixels which is continuously integrated forming high resolution images. The forward-view and side-view imaging systems of the FDOT highway evaluation vehicle use DVC-1310c color cameras (Figure 3.4 (b)) that utilize a 2/3-inch Sony ICX085AK interline CCD sensor. This sensor utilizes 1300 x 1030 effective pixels.

Figure 3.4 (a) Front Face of the Line-scan Camera Basler L103 Without Optics; (b) Digital Camera DVC 1310c
3.1.2. Gain and Exposure

In CCD imaging, the gain refers to the level of amplification a given system will produce. Gain is reported in terms of electrons/ADU (analog-to-digital unit). As an example, a gain of 8 associated with a signal means that the Analog-to-Digital Converter (ADC) of the camera digitizes the signal so that each ADU corresponds to 8 photoelectrons.

Usually the factory default gain value is set in the imaging system so that with optimal lighting and exposure setting, the linear output range of the CCD sensor maps to the input range of the ADC. Under these conditions, black color will produce a gray value of 1 from the ADC and white will produce a gray value of 254. Then the amplification of the signal as a multiple of the raw signal from CCD before amplification can be computed as follows:

\[ k = \frac{254 g_{\text{act}}}{c_{\text{full}}} \]  

(3.2)

where \( k \) represents the gain coefficient, \( g_{\text{act}} \) is the actual gain value obtained after amplification of the signal in units of electrons per ADU and \( c_{\text{full}} \) is full the well capacity of the sensor pixel in electrons. As an example if Basler L-103 camera reports a gain of 500 associated with a given image, and the full-well capacity of this sensor based on its pixel size of 10 µm x 10 µm (Table 3.1) is 82,000 electrons, then by using Eqn. (3.2) actual multiplication gain coefficient \( k \) is equal to 1.55. The above concept will be used in Chapter 4 to obtain information on gain.
The gain of a camera can also be selected under software control to meet the needs of a given application. For example, the gain can be increased when the survey of asphalt pavements is conducted under low lighting (photon starved) conditions and a high-sensitivity mode is required. Alternatively, the gain can be reduced when imaging of concrete pavements under bright light conditions is photon-noise limited and when high SNR mode is required.

When the gain setting of a camera is increased, both the signal and noise are amplified resulting in no change in the SNR, as shown in Eqn. (3.5). If \( \mu \) is the mean of all intensity values \( x \) in the image, \( \sigma^2 \) represents their variance, and \( a \) is the signal intensity amplification, then from basic statistics:

\[
\mu(ax) = a \mu(x) \tag{3.3}
\]

\[
\sigma(ax) = a \sigma(x) \tag{3.4}
\]

Based on Eqns. (2.30) and (2.31):

\[
\text{SNR}(ax) = \frac{\mu(ax)}{\sigma(ax)} = \frac{a \mu(x)}{a \sigma(x)} = \frac{\mu(x)}{\sigma(x)} = \text{SNR}(x) \tag{3.5}
\]

Therefore, the gain is not an effective tool for increasing the amount of information contained in the signal from a CCD. Gain only changes the contrast of an existing image. It must be noted that although SNR would not change with a gain, it could hinder contrast between two bright areas because both areas could reach a saturation pixel intensity limit of 255 during amplification of the signal.

At present, more and more digital cameras use on-chip exposure to regulate the conversion of light captured by the pixels. On-chip exposure involves accumulating
photons in the CCD sensor pixel wells over a defined period of time. As photons strike the pixels, a corresponding electron charge is collected in each pixel. This amount of electron charge is directly proportional to the amount of light that has been accumulated from the sample. Once the predefined exposure time has ended, this accumulated electron charge is converted from an analog to a digital signal.

The downward imaging system of the FDOT highway evaluation vehicle, based on its Basler L-103 line-scan camera, is equipped to use two different exposure times: 1/19,000 and 1/40,000 sec. The exposure time is set for each line constituent of the image. Setting the proper exposure time is based on evaluation of the gain used for the previous line captured by the camera. As an example, if lighting becomes too bright, and the gain value was reduced to a preset minimum value and pixels in the captured image are still too bright then the exposure time changes to 1/40,000 second. For Basler L-103, the manufacturer recommends the minimum exposure time of 1/50,000 second.

The following method can be used to determine the proper exposure time for the captured image. The test image for the given exposure time $T$, e.g. 1 sec, has to be captured and analyzed by using an appropriate image processing software, such as ImageJ. The intensity values of brightest and darkest pixels are recorded. As an example, the brightest and the darkest intensity values shown in Figure 3.5 are equal to $I_{\text{max}} = 255$ and $I_{\text{min}} = 80$ respectively. Then, the difference between them ($\Delta$) is equal to $(255 - 80) = 175$. As a rule (Stein 2004), the brightest pixel in the image should not exceed 80% of the maximum intensity value of the grayscale in order for the signal to become non-linear and weak. For a camera which produces 8-bit images, the threshold
value based on 80% criterion is $I_{\text{threshold}} = 205$. Then, the correct exposure $T_{\text{cor}}$ can be obtained as (Stein 2004):

$$T_{\text{cor}} = \frac{(I_{\text{threshold}} - I_{\text{min}})}{\Delta} = \frac{(205 - 80)}{145}(1 \text{ sec}) = 0.71 \text{ sec}$$

(3.6)

Figure 3.5 Example of the Pixel Intensity Values of the Image

3.1.3. Area-scan CCD Sensor

The forward-view and side-view imaging systems of the FDOT highway evaluation vehicle utilize area-scan interline CCD sensors. Interline sensor type has been designed to capture “live” action at 25 frames per second. These sensors move the charges from the sensor elements first sideways into their own charge-transfer region, then down the vertical shift registers and finally out via the horizontal shift register (Figure 3.6 (b)) (Electus Distribution 2004). Inside each cell is a light sensitive pixel element, a very tiny photodiode, together with a charge transfer area that forms part of a long vertical shift register. There are also two control elements called the readout gate and the overflow gate (Figure 3.6 (a)). Moreover, each cell also contains a short section of a long vertical structure called the overflow drain. When light falls on the sensor
Thus, after earlier, this area is actually part of a long vertical shift register, which links all of the charge-transfer areas in a complete column of cells. This shift register is used to transport the charges in each of the charge-transfer areas down the columns, and ultimately out of the chip.

The overflow gate and the drain are designed to prevent the sensor elements from accumulating too much charge, in case the light falling on them is too high due to over-exposure. The idea is that the overflow gate is held at a voltage level where the “retaining wall” on that side of the sensor photodiode is a little lower than on the charge-transfer region side. This means that if the charge builds up to reach that level, any further charge simply flows over the “wall” into the overflow drain, where it is drained away. This system prevents the photodiode from ever completely filling with charge, which would tend to saturate the CCD image.

element, the photons generate charge carriers and as a result a small quantity of charge builds up in that part of the cell. Then after a short time, a voltage pulse is applied to the readout gate which has the effect of lowering the “retaining wall” on that side of the photodiode, allowing the accumulated charge to flow out of the photodiode and into the charge-transfer area. Thus, after the readout pulse, the charge that was generated in the sensor element by the incident light has been shifted into the charge-transfer area alongside. And as mentioned earlier, this area is actually part of a long vertical shift register, which links all of the charge-transfer areas in a complete column of cells. This shift register is used to transport the charges in each of the charge-transfer areas down the columns, and ultimately out of the chip.
Figure 3.6 (a) Basic Structure of the Picture Element Cell of the CCD Sensor; (b) Structure of the Area-scan Interline-transfer CCD Sensor

3.1.4. Line-scan CCD Sensor

The Basler L103 line scan camera used in FDOT highway evaluation vehicle employs CCD sensor chips which provide features such as electronic exposure time control and anti-blooming. The major components in the camera electronics include the CCD sensor, two amplifiers, and two Analog-to-Digital Converters. The pixels in the CCD sensor output voltage signals when they exposed to the light. At readout, accumulated charges are transported from the light-sensitive sensor elements to the CCD shift registers. The charges from even and odd pixels are processed separately in two channels as shown in Figure 3.7. The charges then move from the two lines of shift registers to the output amplifiers where they are converted to voltages proportional to the accumulated charges. The voltages are digitized and transmitted by the camera. The video data is transmitted as a single 8-bit video data stream.
Since the line-scan camera used in the pavement imaging system of the FDOT highway evaluation vehicle is also a CCD camera, it inherits all of the sources of noise that a CCD camera has. In addition, in a line-scan camera, the manufacturer has to assemble the line-scan images together to form one 2D pavement image. Hence additional sources of error may be present in the line-scan CCD camera due to errors in assembling. As seen in Figure 3.7, Basler L-103 processes odd and even pixels separately in two different data streams. Consequently, this process can bring another type of noise as shown in images in Figure 3.8 captured with the FDOT pavement imaging system during the experiment described in Section 4.
3.2 Types of Noise in CCD Cameras

With the understanding how CCD cameras work, now one can classify different types of noise. There are a variety of noise sources present in pavement image data acquired with a Charge-Coupled Device (CCD) line-scan camera. The photo-conversion process by which object light is converted into photoelectrons introduces object-dependent noise characterized statistically as a Poisson random process. Non-ideal effects introduce extraneous electrons that are indistinguishable from object-dependent photoelectrons. Examples of this noise include object-independent photoelectrons, bias electrons, and thermo-electrons and their cumulative effect can be described by the term background count. Read-out noise further contributes to the degradation of images acquired with the CCD camera aboard the pavement imaging systems. This noise is
characterized as a Gaussian random process. The majority of noise sources attributing to
the loss of image quality along with their sources are shown in Figure 3.9.

Figure 3.9 Sources of Noise and the Source of Their Occurrence in Digital Camera

Based on (Snyder et al. 1994), the CCD image data can be described by following
mathematical model:

\[ r(j) = n_{obj}(j) + n_b(j) + g(j) \]  \hspace{1cm} (3.7)

where \( r(j) \) is number in electrons acquired by reading out pixel \( j \) of the CCD sensor array, \( n_{obj}(j) \) is the number of object-dependent photoelectrons, \( n_b(j) \) is the number of electrons for background count, \( g(j) \) is readout noise, and \( j \) is the number of pixels in
the CCD camera array. The random variables $n_{obj}(j)$, $n_b(j)$, and $g(j)$ are statistically independent of each other.

### 3.2.1. Object-dependent Noise

#### 3.2.1.1. Photon Noise

Today, the use of modern CCD cameras, such as the forward-view and pavement cameras of FDOT highway evaluation vehicle is common. The CCD sensor inside the camera is an array of photosensitive elements, each one of which generates photoelectrons in response to light and stores them as a charge. Photons incident on the CCD chip convert to photoelectrons within the device’s silicon layer. Since light consists of discrete photons that do not arrive at a camera sensor in a steady stream, the number of photons collected on a sensor within a given time interval is a random variable. Therefore photoelectrons constitute not just the signal, but also carry statistical variation in the photon arrival rate at a given point. Modern CCD cameras are sensitive enough to count the individual photons within a finite time and hence the photon noise is introduced into the signal (Young et al. 1998). Most of the observations made about noise and its various sources hold equally well for other imaging modalities such as Complementary Metal Oxide Semiconductor (CMOS) sensors or photographic film.

The photon noise problem arises from the fundamentally statistical nature of photon production which is governed by the laws of quantum physics. The quantification of photons must be limited to only an average number within a given observation time window. The probability distribution of $p$ photons in an observation window of length $T$
seconds can be closely approximated by a Poisson distribution, with a mean of $\rho T$ where $\rho$ is the photon flux, an intensity rate parameter measured in photons per second. Therefore, the number of photoelectrons collected by a CCD pixel also follows a Poisson distribution which has the property that its variance is equal to its mean, i.e. $\sigma^2 = \mu$.

Therefore the relationship between the signal and noise can be written as:

$$\omega_{p,n} = \sqrt{x_{m,n}}$$ (3.8)

where $x_{m,n}$ represents signal constituted by the photoelectrons collected inside the CCD pixel.

Therefore, as an example, for given lighting conditions if the photon flux is 9000 photons per pixel per second, the CCD sensor captures 9 photons per pixel per exposure time ($T$) of 1 millisecond. For this exposure time, the photon noise will represent $\sqrt{9} = 3$ photons, or 33.3 % of the signal. But if the exposure time is prolonged to 0.1 second, the noise will represent $\sqrt{900} = 30$, or 3.3%. Thus, as the exposure time increases, the effect of the noise on the signal can be ignored. Then the signal-to-noise ratio for an image with Poisson noise is given by:

$$SNR_{Poisson\ process} = \frac{\mu}{\sigma} = \frac{\mu}{\sqrt{\mu}} = \sqrt{\mu}$$ (3.9)

where the standard deviation, or noise $\sigma = \sqrt{\mu} = \sqrt{\rho T}$.

Based on Eqn. (3.9), one can conclude that even if there are no other noise sources in the imaging sequence, the statistical fluctuations associated with photon
counting over a finite time interval $T$ would still lead to a finite signal-to-noise ratio (SNR).

Even though photon noise cannot be reduced via camera design (Roper Scientific 2004), it can be minimized through the imaging method. For very bright signals, for which $\rho T$ exceeds $10^5$, the photon noise, or fluctuations due to photon statistics, can be ignored if the sensor has a sufficiently high saturation level. This can be achieved by increasing the exposure time of an image thus capturing more photons. Generally, the pixels in CCD cameras have a finite well capacity reaching their limit at saturation level. It defines the amount of the charge an individual pixel can carry before saturating. Full well capacity depends upon the pixel size of the CCD, the operating voltage used on the CCD, and the aperture of the camera lens. Basler L-100 line scan camera used in the pavement imaging system of the FDOT highway evaluation vehicle uses one pixel line CCD sensor with a pixel size of 10 x 10 µm. Since the manufacturer of the L-100 digital camera does not provide information regarding the full well capacity, typical full well capacity for a camera with a pixel size of 10 x 10 µm had to be derived from the data provided by Roper Scientific (Roper Scientific 2004) as shown in Table 3.1. It is seen that the full well capacity of this camera is large enough to handle longer exposure times. However the maximum exposure time is limited because of the rate at which the camera has to capture images to suit the vehicle speed.
Table 3.1 Full Well Capacity of Three Given Cameras (Courtesy of Roper Scientific) and Computed Value for Basler L-100 Camera

<table>
<thead>
<tr>
<th>CCD Type</th>
<th>Pixel size (µm)</th>
<th>Typical Full Well (e⁻)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kodak KAF1401E</td>
<td>6.8 x 6.8</td>
<td>45,000</td>
</tr>
<tr>
<td>Basler L-100</td>
<td>10 x 10</td>
<td>82,000</td>
</tr>
<tr>
<td>Marconi CCD37-10</td>
<td>15 x 15</td>
<td>165,000</td>
</tr>
<tr>
<td>Kodak KAF1000</td>
<td>24 x 24</td>
<td>630,000</td>
</tr>
</tbody>
</table>

3.2.1.2. Thermal Noise

Normally, lights falls on the CCD and interacts with the silicon layer of the sensor and free up electrons. These electrons are then moved out of the CCD and counted by the ADC. Besides light there are several ways electrons can leak into the pixel without light. The dominant source of these electrons is dark current. Electrons freed from the CCD material itself through thermal vibration get trapped in the CCD well and become indistinguishable from "true" photoelectrons. The thermal noise due to the dark current of the CCD is about 1 electron per pixel per second if the chip temperature is 0°C (Stein 2004). As the exposure time $T$ increases, the number of thermal electrons increases. Dark current describes the rate of generation of thermal electrons at a given CCD temperature. The probability distribution of thermal electrons is also a Poisson distribution where the rate parameter ($\rho$) is an increasing function of temperature. Thermal noise is the square root of the number of thermal electrons generated within a given exposure time and can be written as:

$$\omega_{\text{th}} = \sqrt{DT} \quad (3.10)$$

where $D$ represents the dark current and $T$ represents exposure time interval.
As a measure of the thermal noise, one can look at the time necessary to produce a sufficient number of thermal electrons for the image to move from one brightness level to the next in the absence of photoelectrons striking the sensor through the optics. This last condition, the absence of photoelectrons, is the reason for the name dark current. Mapping of pixels that have some source of signal other than light can be achieved by taking *dark frame* image (Figure 3.10 (a)). It is an image with an exposure of several minutes but without any light allowed to strike the CCD sensor taken at the same temperature. Moreover, dark frame also can show the on-chip amplifier circuit emitting photons onto the CCD array due to the heating by the amplifiers themselves, which can be seen in the lower left corner of the Figure 3.10 (b). With the voltages required for read-out, the intensity of the light can become quite high and can affect the ability to capture images correctly.

![Figure 3.10 (a) Example of Dark Frame Image; (b) Dark Frame Image Showing Luminance Due to the On-chip Amplifier](image)
There are alternative techniques for suppressing dark noise and these usually involve estimating the intensity difference corresponding to the average dark current for the given exposure time and then subtracting this value from the CCD pixel intensity values before the ADC processing occurs. While this technique does reduce the dark current average, it also reduces the possible dynamic range of the signal.

To achieve the most favorable working conditions for an imaging system, it can be maintained in favorable temperature conditions using a fan and a sensor mounted inside the camera enclosure, as shown in Figure 3.11. This technique is employed in the forward-view, side-view, and pavement imaging systems of the Florida DOT highway evaluation vehicle.

Figure 3.11 Details of the Cooling Fan for Forward-View Imaging System of FDOT Highway Evaluation Vehicle
Other cooling techniques are based upon Peltier cooling elements with which it is straightforward to achieve temperatures difference up to 130° K depending on the element type and air humidity (Norton 2004). Peltier cooling elements are based on pumping the heat from one side of 2-semiconductor element to the other, utilizing the Peltier effect. The principle of Peltier cooling elements is shown in Figure 3.12 (a) while its structure is shown in Figure 3.12 (b). If one places a drop of water in the hollow on the joint of p-type (such as antimony Sb) and n-type (such as bismuth Bi) semiconductors, and switch on the current, the drop would freeze, and, with the reversal of the direction of the current the drop would melt (Rudometov and Rudometov 2004). This cooling technique leads to low thermal electron production rates. If night time surveys are performed during hot summer nights when outside temperatures are high, dark or thermal noise may grow large enough to become large enough to influence the quality of the pavement image.

![Figure 3.12 Peltier Cooling Element: (a) Principle; (b) Structure](image-url)
3.2.1.3. Bias Noise

There is a certain amount of electric potential difference that must be imposed on the chip so that each pixel can act as a photosensitive pixel able to gather electrons. The result of applying a potential difference on the chip causes an electron build-up in the pixels, even if no light is incident on the CCD sensor. The number of bias electrons remains constant no matter how long one exposes the CCD chip, as long as the potential difference applied on the chip does not change.

To evaluate the bias noise, *bias frame* (Figure 3.13) is captured with a zero exposure time and no light striking the CCD (with the shutter closed). Moreover, the bias frame also determines the amount of the read-out noise described in Section 3.2.2.1 since an image of bias frame that captures bias noise is also affected by the noise due to the read-out of the sensor. If zero-length exposure is not allowed by capturing software, the use of the shortest possible exposure time is a solution. The histogram of a typical averaged bias frame reveals a Gaussian distribution (Howell 2000). The intensity of pixels in a bias frame should have an average value somewhere above zero and randomly varying among pixels. It is important that no pixel in a bias frame image has an intensity value of zero which represents a value that was outside the lower range of the ADC that processes the analog signal from the sensor and thus the pixels will have no signal and therefore no statistical information on it.
3.2.2. Object-independent Noise

3.2.2.1. Read-out Noise

Another type of signal independent noise is read-out noise. All electronic noise sources inherent to the digital camera and the CCD sensor are collectively referred to as read-out noise and it represents the error introduced during the process of reading the signal from the sensor, in this case through the field effect transistor (FET) of a CCD chip. The read-out noise of a typical CCD camera is about 15 electrons per pixel for every read-out process (Stein 2004). Read-out noise for a given imaging system can be evaluated by capturing the bias frame described in Section 3.2.1.3. The standard model for this type of noise is additive, Gaussian, and independent of the signal.

As mentioned in Section 1.1.2 since the line-scan sensor is a CCD sensor with one line of pixels, the same concepts apply to line-scan cameras as well. This noise is present even at exposure times of zero length. The magnitude of this noise varies with the gain and also over time. A major component of read-out noise arises from the on-chip
amplifier and it can be reduced to manageable levels by appropriate read-out rates and proper electronics.

3.2.2.2. Quantization Noise

Noise that occurs in the analog-to-digital converter (ADC) is called quantization noise. The noise is additive and independent of the signal when the number of image bits $B \geq 4$. This is equivalent to a number of gray levels of $L \geq 2^B$ or $L \geq 16$. For a signal that has been converted to an electrical form and thus has minimum and maximum voltage values, the ADC is adjusted so that zero corresponds to the minimum voltage value and $2^B - 1$ corresponds to the maximum voltage value. The following equation for SNR can be used to evaluate the quantization noise ($q_n$) (Young 1998):

$$SNR_{q_n} = 6B + 11 \text{ dB}$$  \hspace{1cm} (3.11)

Quantization noise can usually be ignored as the overall SNR of a complete imaging system is typically dominated by the smallest SNR. The overall magnitude of the SNR for forward-view and pavement imaging systems of the FDOT highway evaluation vehicle are given in Table 3.2 for the best and worst cases. Forward-view camera had been tested in November 2003 for different aperture settings and the pavement camera was tested in May 2004 for different pavements, lighting conditions, and speeds. For example, the maximum SNR for the line-scan camera used in the FDOT highway evaluation vehicle with a preset JPEG (8-bit) image format depends on the quantization noise. Based on Eqn. (3.11), max. $SNR_{\text{line-scan}} = 6(8) + 11 = 59dB$. 

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Table 3.2 Magnitude of the Best and Worst SNR for Forward-View and Pavement Cameras of FDOT Highway Evaluation Vehicle

<table>
<thead>
<tr>
<th>Camera Conditions</th>
<th>Average SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Forward-View</strong></td>
<td></td>
</tr>
<tr>
<td>Aperture F4.0</td>
<td>50.8</td>
</tr>
<tr>
<td>Aperture F8.0</td>
<td>35.7</td>
</tr>
<tr>
<td>Aperture F1.5</td>
<td>39.9</td>
</tr>
<tr>
<td><strong>Pavement (line-scan CCD)</strong></td>
<td></td>
</tr>
<tr>
<td>Concrete pavement, sunny, pavement lights ON</td>
<td>28.5</td>
</tr>
<tr>
<td>Concrete pavement, mostly sunny, pavement lights OFF</td>
<td>30.4</td>
</tr>
<tr>
<td>Asphalt pavement, sunny with shadow overcast, pavement lights ON</td>
<td>20.0</td>
</tr>
<tr>
<td>Asphalt pavement, sunny with shadow overcast, pavement lights OFF</td>
<td>30.4</td>
</tr>
<tr>
<td>Asphalt pavement, cloudy, pavement lights ON</td>
<td>33.1</td>
</tr>
<tr>
<td>Asphalt pavement, cloudy, pavement lights OFF</td>
<td>34.1</td>
</tr>
</tbody>
</table>

3.2.2.3. **Noise Due to the Optical System and Defects on the CCD Sensor**

In a CCD sensor, the most common noise sources due to the optical system are vignetting and shadows from out-of-focus dust specks in the optical system and on the sensor. Moreover, most CCD sensors will have a few pixels that do not respond to light properly due to some defects in the CCD structure that occurs during the manufacturing process. The result is that those pixels are not as sensitive to the light as the surrounding pixels and therefore they appear dark. Another form of defect that can affect the ability to recognize pavement features is the column defect due to bad pixels that can trap or drain charge away resulting in dark spots. As the image is read from the CCD, the charge must be pushed from pixel to pixel in the vertical direction. As each pixel spends time in the
bad pixel, it is drained of charge. Thus each pixel below the trap becomes dark as shown in Figure 3.14.

![Figure 3.14 Example of Column Defect in a Flat Frame Image](image)

If the image is captured with an evenly diffused light source, also called the *flat frame* (Figure 3.15 (a)), the noise due to the optical system (Figure 3.15 (b)) as well as any defects on the CCD (Figure 3.14) will unveil. To obtain a flat frame image, one has to place the camera face up with the window of the optics exposed. The light can be diffused by placing one or more white paper sheets over the optical lens. The key is to take a shot with the exposure time high enough to achieve an average intensity level (128 for a 8-bit camera) in the image with magnitude of half the maximum intensity level (256 for a 8-bit camera). Exposure lengths of 0.5 – 2.0 seconds are ideal with an average intensity values in the image of 1,000 to 3,000 for a 12-bit camera producing 4,096 different intensity levels or 10,000 to 40,000 for a 16-bit camera which is able to differentiate 65,536 intensity levels.
3.2.2.4. Compression Noise

In addition to noise added inherently by the sensor, image processing techniques also corrupt the image with noise. Very often, the raw image acquired by the sensor is processed using various operations such as filtering, compression, enhancement, and etc. The JPEG image format is the predominant format used by digital cameras among others such as BMP or TIFF. Even professional cameras have a JPEG (Figure 3.16) mode despite its significant compression which allows high compressions at the expense of loss of information. This compression algorithm has become the *de facto image format* for electronic storage of photographic images mainly due to its ability to reduce an image file size by a ratio of 8:1 to 10:1 without any degradation in image quality to the human eye at normal viewing magnification. This compression algorithm is based on the fact that humans have only a restricted capability to perceive high frequencies. The more densely
one compresses the file, the more information one loses and the more artifacts are created in the image. JPEG is particularly susceptible to artifacts because of the way it attempts to maintain details (edges) against large plain color areas (Askey 2003). Because JPEG analyzes the image in 8 by 8 blocks, these artifacts can sometimes appear with sharp "square" edges. Furthermore, JPEG cannot handle very noisy images effectively because of the excessive amount of information in a very noisy image that JPEG has to discard thus introducing more artifacts.

![Figure 3.16 JPEG Artifacts from Pavement Image (zoomed-in) where Lines Demarcate 8 by 8 Pixel Blocks Processed by JPEG Algorithm](image)

If the image contains features that are one dimensional such as hairline cracks, compression artifacts can lower the edge contrast between the crack and the background. They can also create “phantom” features with contrast high enough to be wrongly recognized as cracks when analyzed manually or using automatic means.
3.2.3. Effect of Saturation

A CCD pixel can contain only finite number of electrons, about $3 \times 10^5$ (Morrison 2004). The capacity of each pixel is referred to as full-well capacity. If a pixel is illuminated by a bright object and/or if the exposure time is long enough, the well will start to fill and the photometric response of the pixel departs from linearity and random noise starts to be clipped at the top end. Once this capacity is reached, saturation occurs. The 12-bit ADC of the CCD camera saturates at about $4.1 \times 10^5$ electrons and any charge above this level is lost. If the saturation level exceeded the full-well capacity, the charge begins to spill into adjoining pixels. Because the barriers defining the pixel are lower in the parallel direction, the spill occurs along the parallel register of the CCD as shown in Figure 3.17(a). Thus the vertical blooming spikes called parallel saturation (Figure 3.18(a)) occur. In most CCD sensors, the capacity of the serial register pixels is designed to be twice the capacity of the parallel register pixels. In some CCD sensors, it is possible to exceed the charge capacity of the serial register and then serial saturation occurs (Figure 3.18(b)).

It was recognized that forward-view and side-view imaging systems of the FDOT highway evaluation vehicle can suffer from the saturation problem if strong light sources, such as ones bounced from moving vehicles in front of highway evaluation vehicle, enter the lens, as shown in Figure 3.17(b).
If the saturation occurs during exposure, it is also possible to exceed the capacity of the serial register pixels as well. When this occurs, charge begins to spill along the serial register, usually in the horizontal direction. In most CCD sensors, the capacity of the serial register pixels is designed to be twice the capacity of the parallel register pixels. The saturation of the CCD sensor should occur near the saturation level of the ADC, which for a 12-bit camera must be close to an intensity value of 4095. If not, the camera
would have an adjustment problem which has to be corrected by the camera manufacturer.

To minimize this saturation effect, manufacturers implement a special drain to draw off these excess electrons before they can spill into adjacent pixels. The price for implementing the anti-blooming drains is that they take up room in the CCD structure and consequently lead to lower full well capacity.

3.2.4. Effect of Flare

When a light from a strong light source is incident on the optics of the camera, flare may occur on the image. Flare can occur even if the strong light source is not included in the image. The phenomenon of flare occurs due to light bouncing off the glass surface of the lens as shown in Figure 3.19, i.e. internally reflecting, rather than transmitting through. Flare represents itself in two different forms (1) contrast deterioration (flare) and (2) ghosting. Flare shown in Figure 3.20(b) is seen as a washed-out area near the bright spot on the image while ghosting (Figure 3.20(c)) appears like a string of dots, in a color image usually of green, purple, or violet color, that has the shape of the aperture of the lens and is not a part of the actual scene. Sometimes, flare can represent itself as an evenly fogged image shown in Figure 3.20(c) with veiling glare causing a lowering of the overall image quality. Most wide angle lenses suffer from this problem. Because of this internal reflection, image contrast and tonality are degraded.
To decrease the problem due to direct sunlight, the glass surface of good quality lenses is multicoated with special anti-reflection chemicals to prevent flare and ghosting. However, even with multicoated lens, flare cannot be eliminated completely. To overcome flare due to parasitary light sources outside the image, the field of view can be blocked using a lens hood.

Figure 3.20 (a) Flare in the Pavement Image of the Standard Grayscale Target; (b) Example of Flare that Produces Low Readability of the Text; (c) Example of Heavy Flare Problem Resulting in Ghosting (on the left) and Veiling Glare
On forward-view images of the FDOT highway evaluation vehicle, the effects of flare and ghosting were encountered especially when direct sunlight entered the lens of the forward-view and side-view cameras. This problem was significantly reduced by designing a lens hood for these cameras (Mraz et al. 2004). Also, the pavement imaging system of the FDOT highway evaluation vehicle would suffer from flare if a strong light source directly enters the lens while capturing the standard grayscale target as shown in Figure 3.20(a).

3.3 SNR (Signal-to-Noise Ratio)

A good estimation of SNR can be achieved by using the CCD equation for SNR (Roper Scientific 2003):

\[
\frac{S}{N} = \frac{\rho Q_e T}{\sqrt{(\rho + R_{\text{bg}}) Q_e T + \left[ DT + \left( N_e^2 \right) \right]}}
\]  

(3.12)

where \( \rho Q_e T \) represents the signal from the object of interest, i.e. crack and \( \sqrt{\rho Q_e T} \) represents the photon noise due to uncertainty of the incoming light from the object. The signal of the object of interest can be written using the average photon flux incident on the CCD, \( \rho \) per pixel per given exposure time interval \( T \). The photons entering one pixel of the CCD must be multiplied by the quantum efficiency \( Q_e \) of the CCD camera to determine the number of electrons detected, as described in (Deiries 2004). \( R_{\text{bg}} \) represents number of photons per pixel per second from the background that can arise from many sources and is usually scattered light that is not of interest to the observer. The number of the photons has to be multiplied by the \( Q_e \) and it exhibits a Poisson distribution having a
square root relationship between the signal and noise. \( D \) is the electrons per pixel per second due to dark current, and \( N_r^2 \) is readout noise in units of root mean square electrons (electrons RMS) per pixel. The larger the SNR, the stronger the signal and/or the lower the noise, the more desirable the image quality is.

Under low-lighting conditions, read noise exceeds photon noise and the image is said to be \textit{read-noise-limited}. If the read noise is the dominant noise for short exposure times \( T \), Eqn. (3.12) can be simplified to the form:

\[
\frac{S}{N} = \frac{\rho Q T}{N_r}
\]

Another question that can arise is how the light reflected from the pavement surface affects the quality of the image. Figure 3.21 shows three cases with two sources of the light:

(1) sunlight, and

(2) light from the pavement lighting system which is preset to illuminate the pavement area captured by the line-scan camera at a fixed orientation.

The only variable here is the position of the sun during the survey. Figure 3.21 also shows how a combination of both sources of light will affect brightness of the crack on the image. In all of these cases, the actual crack width is not clearly seen in the image. This is worse when the sunlight is not directly above. By using the improved filtering algorithm described in Section 3.5 and 3.6 the border of dark (internal part of the crack) and the bright (background pavement surface) areas can be enhanced.
If the integration time is prolonged, photon noise exceeds both read noise and dark noise, and at this point the image is said to be photon-noise limited. Then, Equation (3.12) can be written as:

$$\frac{S}{N} = \frac{\rho Q_c}{\sqrt{(\rho + R_{yy})Q_c + D}} \sqrt{T}$$  (3.14)

An example of the relation between SNR and exposure time for a digital imaging system is shown in Figure 3.22 where the points computed using Eqn. (3.12), (3.13), and (3.14) are respectively represented by boxes, a solid line fitting the computed points for shorter exposure times, and the dashed line fitting the computed points for longer exposure times. The intersection of Eqns. (3.13) and (3.14) divides the graph into two sections, read-noise-limited and photon-noise limited regions.
The SNR increases linearly with exposure time $T$ if the mean pixel value is within the read-noise-limited region (Roper Scientific 2003). A single 1.0-second exposure has about ten times the SNR of a single 0.1-second exposure in this region. However, adding together multiple exposures increases the SNR by the square root of the number of exposures. Therefore, if ten 0.1-second exposures are taken, SNR will increase by a factor of three. On the other hand, in the photon-noise-limited region, the SNR increases only as the square root of the exposure time $T$ and 100-second exposure has essentially the same SNR than ten exposures of 10-second duration. For the cameras used in the FDOT highway evaluation vehicle, SNR could fall in any of the two regions depending on lighting conditions and the camera settings.
3.4 Mathematical Representation of the Noise in the Signal

Ideally, each pixel in the CCD sensor must have exactly the same response in the form of the intensity value for uniform light striking the sensor. In reality, the intensity of each pixel is a little above or below this ideal value by some random factor or noise that is added to each pixel in the image.

The level of noise present in an image can be reduced conveniently if the scene is static. However, dynamic modes can be considered as quasi-static, if the movement of the vehicle is negligible in comparison to the short exposure time during which the image is captured. This is because the noise distribution in a static image can be regarded as approximately symmetrical with a mean of zero (Efford 2000). As a result, positive perturbations of the intensity value of a pixel by a given amount are just as likely as negative perturbations by the same amount, and hence there will be a tendency for these perturbations to cancel out when several noise values are added.

Photon noise can be modeled with multiplicative or non-linear models. Then the Poisson distribution modeling photon noise can be expressed as:

\[ P(p | \rho, T) = \frac{(\rho T)^p e^{-\rho T}}{p!} \quad (3.15) \]

where \( P \) is a probability of having \( p \) photons strike the sensor during a time interval \( T \) and \( \rho \) is the photon flux, an intensity rate parameter measured in photons per second.

A Poisson distribution is similar to a Gaussian distribution except that it is used for discrete random variables, applies only to non-negative quantities, and has the
property that its variance is equal to its mean, i.e. $\sigma^2 = \mu$. Moreover, Poisson distribution is generally non-symmetric and therefore the maximum or the peak does not correspond to the mean value. However, as $\mu$ becomes large (Figure 3.23) the distribution becomes more and more symmetric and approaches a Gaussian form. The probability density function of Gaussian noise can be expressed by:

$$p(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

(3.16)

where $x$ is the intensity of the sampled signal, $\mu$ is its mean and $\sigma$ is its standard deviation (noise).

For $\mu \geq 20$, a Gaussian, in fact, becomes a relatively valid approximation and can be used in place of a Poisson distribution in numerical modeling of noise. When $\mu < 20$, modeling of photon and thermal noises becomes mathematically complicated, and therefore the noise in the imaging system is usually assumed to be signal independent only (Fisher et al. 2000). Another main source of noise, read noise, is distributed about the ideal value following the Gaussian distribution.
Therefore, based on the Eqn (3.7), the intensity of a digital image captured by an imaging system containing noise can be modeled as:

\[ z_{m,n} = x_{m,n} + \omega_{m,n} \quad (3.17) \]

where \( z_{m,n} \) represents the intensity of the image, \( x_{m,n} \) the intensity of a noiseless image, and \( \omega_{m,n} \) the resulting Gaussian noise on a pixel defined by \((m,n)\).

Noise is often described by the variance of pixel intensities in an area of an image with a more or less uniform brightness. The variance of pixel intensities, which is a direct measure of the noise shown in Figure 3.2, can be defined as:

\[
\sigma^2 = \frac{\sum (z - \mu)}{N - 1} \quad (3.18)
\]
where \( z \) represents intensity values in the image, \( \mu \) represents the mean intensity value of the image, and \( N \) represents number of pixels in the image.

By defining noise in pavement image based on Eqn. (3-17), the noise removal technique based on local statistics filtering can be used, as described in following chapters.

### 3.5 Noise Filtration

Some simplest image enhancing operations, also called linear mapping, involve the adjustment of brightness, contrast, or color in an image. A common reason for linear mapping manipulations that modify a pixel’s intensity value independently of all other pixels is the need to compensate for difficulties in image acquisition, such as underexposition. The simplest operation on single pixels is linear mapping where the overall adjustment of brightness (\( b \)) and contrast (\( c \)) is made. Brightness is defined as a relative expression of the intensity of the energy output of a visible light source while contrast is defined as a variation in intensity of an image formed by an optical system. General expression for brightness and contrast modification is:

\[
g_{m,n} = c \cdot z_{m,n} + b
\]  

(3.19)

where \( g_{m,n} \) represents post-processed intensity value for a given pixel and \( z_{m,n} \) is the original intensity value of the pixel under the consideration.

If the brightness \( b > 0 \), the overall brightness is increased and if \( b < 0 \), it is decreased. Similarly, if \( c > 1 \), the contrast is enhanced, whereas if \( c < 1 \), it is reduced. Brightness and contrast modification are the simplest image processing operations that
can be applied to a pavement distress image to improve its overall quality. This will magnify the tiny residual variations in contrast to reveal enough detail to allow proper interpretation of the features, such as cracks.

An isolated pixel carries information on the intensity and color but it cannot express any information about the way in which these properties vary spatially. Therefore, processes such as linear mapping cannot be used to investigate or control spatial variations in image intensity or color noise. To be able to minimize these variations, the variation of intensity over a designated area of the image has to be evaluated. Therefore, the upgraded intensity value of a pixel has to be computed from its original value and the intensity values of pixels in its vicinity. These neighborhood operations are more costly in terms of computing time than single point processes, but they facilitate the achievement of a range of useful effects, including noise filtering.

One of the fundamental neighborhood operations of image processing is convolution. This operation can be used to filter images and suppress noise. In convolution, the weighted sum of intensity values, or grey levels, from the neighborhood surrounding that pixel is evaluated. The neighborhood includes the pixel under consideration, and it is customary for it to be disposed symmetrically about the considered pixel (Efford 2000). Then, obviously the neighborhood has to have odd dimensions, e.g. 3 x 3, 5 x 5, 7 x 7, etc. Although the neighborhood does not need to be a square, a square neighborhood is selected usually since there is rarely any reason to bias the calculations in the x or y directions.
In this approach, the intensity values of the neighborhood of the considered pixel are weighted by coefficients that are elements of a matrix called the *convolution kernel*. Thus, the kernel’s size defines the size of the neighborhood where the evaluation takes place and it is centered on the pixel of interest. The size of the kernel has to be small relative to the image size. During convolution, each kernel coefficient is multiplied by an intensity value from the neighborhood of the image lying under the kernel. The kernel is applied in such way that the value at the top-left corner of the kernel is multiplied by the value at the bottom-right corner of the neighborhood. This summation can be generally expressed for a $p \times q$ kernel as:

$$
g_{m,n} = \sum_{k=-q}^{q} \sum_{j=-p}^{p} h_{j,k} z_{m-j,n-k}
$$

(3.20)

where $p$ and $q$ are odd numbers that represent the width and the height of the kernel respectively, $h_{j,k}$ defines the kernel, $g_{m,n}$ and $z_{m,n}$ represent the updated and the original intensity values respectively, of the pixel under consideration. This kernel is then successively moved across the image until every pixel has been operated on. For the example of the kernel and the neighborhood illustrated in Figure 3.24, the operation in Eqn. (3.20) can be expressed as:

$$
g_{m,n} = \sum_{k=-1}^{1} \sum_{j=-1}^{1} h_{j,k} z_{m-j,n-k}
$$

(3.21)

and the result of the convolution operation can be expressed by the modified intensity of the pixel $(0,0)$ as:

$$
g_{0,0} = (-1 \times 82) + (1 \times 88) + (-2 \times 65) + (2 \times 76) + (-1 \times 60) + (1 \times 72) = 40
$$
If the kernel $h_{j,k}$ is defined appropriately, $g_{0,0}$ represents the intensity of the pixel $(0,0)$ with reduced noise.

After the convolution operation, the new image $g$ has to be created to store the results of the convolution because application of convolution to any pixel except the first pixel would make use of intensity values already altered by a prior convolution operation.

Any convolution kernel where all the coefficients are positive will act as a low pass filter. In the simplest case, all coefficients in the kernel are equal and their sum is equal to 1 so that the kernel is normalized (Eqn. (3.22)). Thus the convolution operation will ensure that the upgraded intensities of all pixel lie in the range of $(0 – 255)$.

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 0.111 & 0.111 & 0.111 \\ 0.111 & 0.111 & 0.111 \\ 0.111 & 0.111 & 0.111 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 0.111 & 0.111 & 0.111 \\ 0.111 & 0.111 & 0.111 \\ 0.111 & 0.111 & 0.111 \end{bmatrix}$$

(3.22)
Convolution with normalized kernels is therefore equivalent to computing the mean gray level value (intensity) over the neighborhood defined by the kernel. For this reason, these kernels are also called mean filters. Although median filters suppress noise in an image, they do not eliminate it. Moreover, they can also blur the objects of interest, such as cracks in a pavement, making their edges less well defined because this technique is based on the assumption that most points in an image are spatially coherent with their neighbors, a hypothesis that is not valid at the edge or feature points such as cracks (Owens 1997). Therefore use of an alternative noise filtering algorithm based on the use of local statistics developed by Lee (Lee 1981) is more applicable in enhancing of pavement distress or crack images. This technique is based on the use of local mean and variance without the need for the modeling of the original image required by other methods such as Kalman or Wiener filtering techniques (Lee 1981). The only assumption is that the sample mean and variance of the intensity of a given pixel are equal to the local mean and variance of the pixels within a fixed neighborhood surrounding it. This assumption is generally valid in low-contrast areas where the estimated pixel intensity value approaches the local mean intensity value.

To ensure that this algorithm works in high-contrast areas, where cracks occur, redefinition of the neighborhood is implemented, in which the variation of the local means and variances are tracked. This technique is based on accounting for the orientation of the edge, or incorporation of the local gradient into the local-mean and local-variance filtering algorithm. For each pixel with a high local variance or high contrast over a preset threshold, a gradient is computed in the local area in different
spatial orientations to obtain the orientation of the crack edge. Then two subsets of pixels in the local areas on each side of the crack edge are defined. It has to be first determined to what subset the pixel under consideration belongs. Since the required subset contains pixels only on one side of the edge, the local mean and variance computed in this subset must more precisely represent the mean and variance of the pixel under consideration.

3.6 Filtering Method Based on Local Statistics

As shown in Eqn (3.17), noise in a two-dimensional \( N \times N \) image can be modeled as
\[
z_{m,n} = x_{m,n} + \omega_{m,n}.
\]
In most filtering algorithms, the apriori mean and variance of \( x_{m,n} \) is obtained from an assumed noise model while in the local-statistics method the apriori mean \( \bar{x}_{m,n} \) and the variance \( Q_{m,n} \) are approximated by the local mean \( \bar{z}_{m,n} \) and variance
\[
E\left[\left(z_{m,n} - \bar{z}_{m,n}\right)^2\right]
\]
of all pixels in the neighborhood surrounding \( z_{m,n} \) as:
\[
\bar{x}_{m,n} = \bar{z}_{m,n}
\]
and:
\[
Q_{m,n} = E\left[\left(z_{m,n} - \bar{z}_{m,n}\right)^2\right] - \sigma^2
\]
where \( \sigma^2 \) represents the noise variance or \( \omega_{m,n} \) in general form.

Under this assumption, the minimum-square filter (Lee 1981) giving the estimated pixel intensity value before degradation, \( \hat{x}_{m,n} \), can be obtained as:
\[
\hat{x}_{m,n} = \bar{x}_{m,n} + k_{m,n} \left(z_{m,n} - \bar{z}_{m,n}\right)
\]
where:
\[ k_{m,n} = \frac{Q_{m,n}}{Q_{m,n} + \sigma^2} \] (3.26)

Since \( Q_{m,n} \) and \( \sigma^2 \) are both positive, \( k_{m,n} \) will lie between 0 and 1. For a low-contrast area, \( Q_{m,n} \) would be relatively small, therefore \( \hat{x}_{m,n} \approx \bar{x}_{m,n} \). On the contrary, in high-contrast areas, \( Q_{m,n} \) is much larger than \( \sigma^2 \) and \( \hat{x}_{m,n} \approx z_{m,n} \). For most noisy images this algorithm produces quite satisfactory results, since human vision is more sensitive to noise in a flat area than in an edge region (Lee 1981). However, in the case of pavement crack images, it is desirable to smoothen out the noise around the edge areas. Thus, an improved filtering algorithm known as the gradient mask method provides a more feasible solution to the computation of the local mean and variance. In this method a subset of the neighborhood, where the pixel under consideration is located, is used for the computation of the local statistics. As it can be seen in Figure 3.25 (a), the point \( x_{m,n} \) is more likely to be a member of the subset of pixels in the unshaded area rather than a member of the entire neighborhood. If the local mean and variance are computed based on pixels in the unshaded subset, the new \( Q_{m,n} \) obtained is considerably smaller than \( Q_{m,n} \) obtained from the entire set. As a result, the noise will be smoothened at the edge.

Then, based on Eqns. (3.25) and (3.26):

\[ \hat{x}_{m,n} \approx \bar{x}_{m,n} \] (3.27)

where \( \bar{x}_{m,n} \) is the local mean of the subset.

To determine the subset to which the pixel under consideration belongs, one has to know the orientation of the crack edge and on which side of that edge the pixel \((m,n)\).
lies. To determine the edge orientation, a $3 \times 3$-pixel local-gradient mask is used. To minimize the noise effect on the local gradient, the $9 \times 9$ window is divided into nine, $3 \times 3$ sub-areas as shown in Figure 3.25 (b) and the local means of each sub-area is computed. Then, the $3 \times 3$ gradient mask is applied to estimate the local means of these sub-areas (Figure 3.25 (b)). To determine the direction of the gradient, Sobel kernels expressed in Eqn. (3.30) are applied to the means of the sub-area as expressed by the following pair of convolution operations (Sonka et al. 1999):

$$g_{x_{m,n}} = s_x * z_{m,n}$$  \hspace{1cm} (3.28)

$$g_{y_{m,n}} = s_y * z_{m,n}$$  \hspace{1cm} (3.29)

$$s_x = \frac{1}{4} \begin{bmatrix} -1 & 0 & 1
-2 & 0 & 2 \\
-1 & 0 & 1 \end{bmatrix} \quad \text{and} \quad s_y = \frac{1}{4} \begin{bmatrix} 1 & 2 & 1
0 & 0 & 0 \\
-1 & -2 & -1 \end{bmatrix}$$  \hspace{1cm} (3.30)

where $z_{m,n}$ represents original intensity values.

Because Sobel kernels contain both positive and negative coefficients, the output can be negative or positive. The $s_x$ kernel is sensitive to intensity changes in the $x$ direction, or to edges running vertically while $s_y$ is sensitive to intensity changes in the $y$ direction, or edges that run horizontally. To keep $g_x$ and $g_y$ values between 0 and 255, the kernels $s_x$ and $s_y$ are normalized by a factor of $\frac{1}{4}$. Gradients $g_{x_{m,n}}$ and $g_{y_{m,n}}$ are components of a gradient vector $\mathbf{g}$ expressed by:

$$\mathbf{g} = \begin{bmatrix} g_x \\
-g_y \end{bmatrix}$$  \hspace{1cm} (3.31)
This vector is oriented along the direction of change and normal to the direction in which the edge runs. The magnitude and direction of the gradient can be expressed as:

\[
g = \sqrt{g_x^2 + g_y^2} \quad (3.32)
\]

\[
\theta = \tan^{-1}\left(\frac{g_y}{g_x}\right) \quad (3.33)
\]

where \(\theta\) is measured relative to the \(x\) axis (Figure 3.26).

The direction of the gradient mask with the maximum absolute value of the gradient is used as the direction of the edge. The directional indices for the gradient mask proposed by Lee (Lee 1981) were refined to evaluate the \(\theta\) for every 15 degrees in comparison to 45 degrees and they are also shown in Figure 3.26.

![Figure 3.25](image)

Figure 3.25 (a) High Contrast Neighborhood of a Pixel; (b) Demarcation of 3 x 3 Sub-areas in the Neighborhood of Pixel in Figure 3.25 (a) (9 x 9)
Once the edge orientation is identified, the mean pixel intensities of the sub-area (Figure 3.27) orthogonal to the edge are compared to determine on which side of the edge the considered pixel \((m,n)\) falls. Subsets corresponding to all of the directions in Figure 3.26 are shown in Figure 3.27. For the example in Figure 3.25 (b), a comparison of 

\[|a_{31} - a_{22}| \text{ and } |a_{13} - a_{22}|\]

determines whether the relevant subset is in direction 3 or 15 (Figure 3.26). If \(|a_{31} - a_{22}| < |a_{13} - a_{22}|\), then subset 15 (Figure 3.28) will be chosen as the one which contains the pixel \((m,n)\). Accordingly, all the pixels in the unshaded area will be used in the computation of the local mean and variance. This will ensure that the intensity variation among pixels of similar brightness would be less marked. Moreover, areas of inherently different brightness would acquire a much higher contrast, perhaps leading to much easier identification of crack boundaries.

![Figure 3.26. Directional Indices](image-url)
For easier implementation of edge orientation identification, a 7 x 7 window is used with each sub-area containing a 3 x 3 pixel matrix overlapping with its neighbors, as shown in Figure 3.29.
Figure 3.28 Definition of Directional Subsets (unshaded areas) on One Side of the Edges
3.6.1. Determination of Noise Variance

In most practical applications, the noise variance $\sigma^2$ (Eqn. (3.24)) is unknown and spatially variant. The noise variance of a local area can be estimated reasonable well by the local variance of a more or less equally intense (flat) area. This idea is implemented in the adaptive filtering technique discussed by Lee (Lee 1981). Another alternative to obtain the noise variance is based on the use of a grayscale target (Figure 3.30). The implementation of this technique should result in a practical noise filtering algorithm that will preclude the need for neither apriori image modeling as in the case of Kalman or Wiener filtering techniques nor the need to use adaptive filtering technique. The latter technique evaluates each pixel in a 7 x 7 window for local mean and variance and then average of five smallest variances determine the noise variance (Lee 1981).
Each patch of the grayscale target represents a flat area (wedge) with a fairly uniform optical density. Because imaging systems used for practical purposes are not ideal systems, noise composed of undesirable signal components that arise from various sources described in Section 3.2 is introduced into the signal. As a result, slight variations in intensity value can occur even within a wedge or patch. Therefore, any variation from the mean value for a given wedge represents the $\sigma^2$ of the noise described in Section 3.6.

![Figure 3.30 Fifteen-wedge Grayscale Target](image.png)

For each wedge, the mean and variance of intensity can be computed using image editing software such as the *ImageJ*, as shown in Figure 3.31 (a) and 3.31 (b).
After the subset mean is computed for a pixel of an image under consideration using the procedure described in the Section 3.6.3, the noise variance of any pixel of the that image is determined through linear interpolation of noise variance values corresponding to the patches with the closest mean intensity. This method should give more precise determination of the true level of noise for a given pixel than the adaptive filtering method which assumes the variance to be the average of the five smallest variances computed from 7 x 7 window in the neighborhood. This would be true if all the pixels used for computation of the mean value and variance were originally represented by the flat area and any change in intensity values was due to noise. On other hand, each wedge of the grayscale target is uniform and any deviation of the signal can be assumed to be caused by the noise. The assumption in this case is that the pixel under
consideration with a given intensity value has the same $\sigma^2$ of the noise as the grayscale wedge with a mean intensity value equal to that pixel. This method also is more efficient than adaptive filtering as there is no need for extra computation of mean and variances for each pixel inside of 7 x 7 window.

3.6.2. Illustration of the Filtering Technique

An example of a vertical noisy edge in a 7 x 7 window is provided to illustrate the application of the concepts discussed in the previous sections. The image is of an Edmund Optics Optical Density Target containing 15 grayscale uniform density steps separated by vertical edges. Minolta DiMage5 was used for capturing this image in a non-compressed TIFF format. The sensitivity of the camera was set to an equivalent of ISO800 at which the noise is most visible. Then, ImageJ’s plugin PhotoES_AM was used for evaluating the mean and variance values for each patch and also for computation of the updated intensity of the pixels considered with respect to the previously described methods.

Figure 3.32 (a) shows a part of the image containing a vertical edge while Figure 3.32 (b) shows a zoomed-in 7 x 7 window of this image with the intensity values for pixels inside the window shown in Table 3.3. The pixel highlighted in Figure 3.32 (b) (4,4) would be chosen for the application of the noise reduction technique discussed above.
Table 3.3 Intensity Values for 7 x 7 Window with the One for the Central Pixel Highlighted

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<tr>
<td>157.39</td>
<td>162.15</td>
<td>161.72</td>
<td>167.25</td>
<td>153.70</td>
<td>125.31</td>
<td>98.71</td>
<td></td>
</tr>
<tr>
<td>157.01</td>
<td>160.04</td>
<td>158.80</td>
<td>153.74</td>
<td>145.85</td>
<td>123.44</td>
<td>85.74</td>
<td></td>
</tr>
<tr>
<td>158.23</td>
<td>158.00</td>
<td>151.85</td>
<td>144.13</td>
<td>137.25</td>
<td>121.57</td>
<td>90.42</td>
<td></td>
</tr>
</tbody>
</table>

The intensity value of central pixel under consideration which has to be filtered is 155.06. If local statistics are used in filtering, the mean of the 7 x 7 area will be \( \bar{x}_{4,4} = 141.29 \) and its variance \( \sigma_{\text{orig}}^2 = 590.74 \).
Next, the 3 x 3 mask described in Section 3.6 is applied to obtain the mean values of the sub-areas \((a_{11}, a_{12}, \ldots, a_{33})\) as shown in Table 3.4.

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>156.9</td>
<td>148.421</td>
<td>120.94</td>
</tr>
<tr>
<td>160.633</td>
<td>158.396</td>
<td>127.942</td>
</tr>
<tr>
<td>158.354</td>
<td>152.699</td>
<td>120.221</td>
</tr>
</tbody>
</table>

Table 3.4 Mean Values of the Sub-areas

By applying Eqns (3.28) – (3.33), the magnitude and direction of the gradient are evaluated as \(g = 34.95\) and \(\theta = -4^\circ\) respectively. The gradient direction of \(-4^\circ\) approximately corresponds to the directional index of 0 (zero) as shown in Figure 3.26. To determine on which side of the edge the pixel under consideration \(a_{22}\) is located, the value of \(|a_{22} - a_{21}| = 2.24\) is compared to the value \(|a_{23} - a_{22}| = 30.45\). Based on the criterion defined in Section 3.6, the pixel under consideration lies on the left of the edge. Hence the directional Subset 12 (Figure 3.28) of the 7 x 7 window in Table 3.3 is used for the estimation of the mean and variance of the pixel (4, 4) highlighted in Figure 3.32 (b). This subset is separately shown in Table 3.5.

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>158.72</td>
<td>155.03</td>
<td>140.17</td>
<td>135.18</td>
</tr>
<tr>
<td>160.24</td>
<td>160.07</td>
<td>153.18</td>
<td>145.01</td>
</tr>
<tr>
<td>166.27</td>
<td>162.37</td>
<td>156.05</td>
<td>149.29</td>
</tr>
<tr>
<td>158.70</td>
<td>163.23</td>
<td>157.82</td>
<td>155.06</td>
</tr>
<tr>
<td>157.39</td>
<td>162.15</td>
<td>161.72</td>
<td>167.25</td>
</tr>
<tr>
<td>157.01</td>
<td>160.04</td>
<td>158.80</td>
<td>153.74</td>
</tr>
<tr>
<td>158.23</td>
<td>158.00</td>
<td>151.85</td>
<td>144.13</td>
</tr>
</tbody>
</table>

Table 3.5 Intensity Values for the Directional Subset 4
The mean intensity \( \bar{\mu}_{\text{sub}4} \) and the variance \( \sigma^2_{\text{sub}4} \) of the Subset 4 are 155.95 and 55.81 respectively which represent a reduction of \( \sigma^2_{\text{orig}} \) by a factor of 10 when compared to the 7 x 7 variance \( \sigma^2_{\text{orig}} \) of 590.74. In the next step, the noise variance \( \sigma^2 \) (Eqn. (3.24)) will be determined using the method described in Section 3.6.3.

3.6.3. Use of the Grayscale Target Procedure

First, the image of the Edmund’s Optics Density Target is captured by a digital imaging system and then loaded into ImageJ imaging software as shown in Figure 3.33.

![ImageJ Loaded with an Image of the 15-wedge Grayscale Target](image)

Figure 3.33 ImageJ Loaded with an Image of the 15-wedge Grayscale Target

In the next step, the mean and variance values are computed for each wedge and the results are shown in Table 3.6 and Figure 3.31(b). If a color image is used, the luminance value of any pixel \( L \) is computed by using Eqn. (2.1). On the other hand, for
black and white digital images, such as the one produced by the pavement imaging system of FDOT highway evaluation vehicle, the intensity values are used directly.

Table 3.6 Mean and Variance of Luminance Values of Each Wedge of the Gray-scale Target (from Fig. 3.31 (b))

<table>
<thead>
<tr>
<th>PATCH</th>
<th>AVE_SCALE_MEAN</th>
<th>AVE_SCALE_VAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1_white</td>
<td>221.67</td>
<td>3.80</td>
</tr>
<tr>
<td>2</td>
<td>206.47</td>
<td>7.55</td>
</tr>
<tr>
<td>3</td>
<td>193.44</td>
<td>12.08</td>
</tr>
<tr>
<td>4</td>
<td>170.08</td>
<td>21.41</td>
</tr>
<tr>
<td>5</td>
<td>144.43</td>
<td>35.61</td>
</tr>
<tr>
<td>6</td>
<td>121.74</td>
<td>49.21</td>
</tr>
<tr>
<td>7</td>
<td>104.50</td>
<td>60.31</td>
</tr>
<tr>
<td>8</td>
<td>94.96</td>
<td>64.60</td>
</tr>
<tr>
<td>9</td>
<td>81.76</td>
<td>70.87</td>
</tr>
<tr>
<td>10</td>
<td>74.44</td>
<td>74.34</td>
</tr>
<tr>
<td>11</td>
<td>65.69</td>
<td>80.27</td>
</tr>
<tr>
<td>12</td>
<td>60.22</td>
<td>83.84</td>
</tr>
<tr>
<td>13</td>
<td>53.37</td>
<td>88.36</td>
</tr>
<tr>
<td>14</td>
<td>50.38</td>
<td>85.63</td>
</tr>
<tr>
<td>15_black</td>
<td>48.39</td>
<td>75.43</td>
</tr>
</tbody>
</table>

With respect to the illustration in Fig. 3.31 (b), since the mean intensity of the Subset 4 where the pixel under consideration belongs, $\bar{x}_{sub4}$, is 156, the corresponding noise variance can be interpolated from Table 3.6 as $\sigma^2 = 29.21$. Then, from Eqn. (3.24), the variance of directional Subset 4 ($Q_{4,4}$) would be 26.6. Finally, by using Eqns. (3.25) and (3.26), the estimated intensity value ($\hat{x}_{4,4}$) for the pixel under consideration (4,4) is 155.5.
3.6.4. Verification of the Filtering Technique

The filtering technique discussed in Section 3.6.3 was coded in *PhotoES_AM* plugin of *ImageJ* software. To verify applicability of the proposed filtering technique, two sets of tests were conducted. First, a synthetic image (Figure 3.34) was created in Microsoft Paint program so that background and feature intensity values are equal to 130 and 42, respectively. Then, by using Add Noise built-in function of the *Jasc Pain Shop Pro* program (Jasc Software 2004), three different amounts of the Gaussian noise (5%, 10%, and 15% of coefficient of variation) were introduced into the original image. Finally, these noisy images were filtered by the *PhotoES_AM* plugin under *ImageJ* image editing software and the SNR for both noisy and filtered images were computed. The results of this test are presented in Table 3.7. The effectiveness of the noise removal technique is illustrated in Figure 3.35.

The second evaluation was based on removal of noise from actual pavement images taken by the FDOT highway evaluation vehicle. Figures 3.36 and 3.37 show results of noise filtration from asphalt and concrete pavements.
Table 3.7 Results of the Noise Filtration Test on Synthetic Image

<table>
<thead>
<tr>
<th>Area</th>
<th>Coefficient Of Variation</th>
<th>Type</th>
<th>SNR Background [dB]</th>
<th>SNR Object [dB]</th>
<th>Improvement Background [dB]</th>
<th>Improvement Object [dB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area 1</td>
<td>5%</td>
<td>Before</td>
<td>29.1</td>
<td>29.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>After</td>
<td>42.1</td>
<td>40.9</td>
<td>13.0</td>
<td>11.9</td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>Before</td>
<td>21.6</td>
<td>21.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>After</td>
<td>35.2</td>
<td>29.9</td>
<td>13.6</td>
<td>8.4</td>
</tr>
<tr>
<td></td>
<td>15%</td>
<td>Before</td>
<td>17.9</td>
<td>18.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>After</td>
<td>32.3</td>
<td>29.7</td>
<td>14.4</td>
<td>11.7</td>
</tr>
<tr>
<td>Area 2</td>
<td>5%</td>
<td>Before</td>
<td>29.1</td>
<td>29.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>After</td>
<td>42.8</td>
<td>38.4</td>
<td>13.7</td>
<td>9.4</td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>Before</td>
<td>21.9</td>
<td>21.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>After</td>
<td>36.3</td>
<td>34.4</td>
<td>14.4</td>
<td>12.7</td>
</tr>
<tr>
<td></td>
<td>15%</td>
<td>Before</td>
<td>17.9</td>
<td>17.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>After</td>
<td>32.2</td>
<td>27.0</td>
<td>14.3</td>
<td>9.3</td>
</tr>
</tbody>
</table>

From the results given in Table 3.7 it can be seen that improved filtering technique based on local statistics and use of grayscale target improves the image quality of the object representing the crack and background more than 9 dB and 13 dB, respectively.
Figure 3.35 Example of Noise Removal from Synthetic Image

(a) noisy image (5%)  (b) filtered image

Figure 3.36 Example of Noise Removal from Pavement Image (concrete pavement)

(a) original image  (b) filtered image
Figure 3.37 Example of Noise Removal from Pavement Image (asphalt pavement)
CHAPTER 4

EXPERIMENTAL EVALUATION OF THE PAVEMENT IMAGING
SUBSYSTEM OF THE FDOT PAVEMENT EVALUATION VEHICLE

4.1 General Description

One important objective of this dissertation research was to determine the accuracy and the reliability of the pavement imaging subsystem with respect to evaluating pavement cracks. In keeping with this objective, an experiment was conducted in Gainesville, Florida on May 18 and 19, 2004 to evaluate the accuracy of pavement images captured by the imaging subsystem of the FDOT highway evaluation vehicle and investigate the effect of noise on the images.

The repeatability and accuracy of the downward camera in imaging cracks was tested under the following conditions:

1. different lighting conditions (sunny, cloudy, and overcast),
2. with and without the pavement lighting system,
3. different vehicle speeds (25 mph, 35 mph, 43-45 mph), and
4. different pavement types (asphalt and concrete).

Table 4.1 describes all different testing conditions under which the experiment was conducted. All the other significant variables such as the aperture etc. were maintained constant. The gain and exposure time were automatically regulated by the capturing software.
Table 4.1 Description of Experiment Conditions

<table>
<thead>
<tr>
<th>Road Name</th>
<th>Direction</th>
<th>Date</th>
<th>Surveying Time</th>
<th>Pavement Type</th>
<th>Lighting Conditions</th>
<th>Pavement Lighting System</th>
<th>Speed [mph]</th>
</tr>
</thead>
<tbody>
<tr>
<td>SR 28</td>
<td>South</td>
<td>05/18</td>
<td>11.33 – 12.15 pm</td>
<td>Concrete</td>
<td>Sunny</td>
<td>On</td>
<td>25, 35, 45</td>
</tr>
<tr>
<td>SR 28</td>
<td>South</td>
<td>05/18</td>
<td>12.19 – 12.35 pm</td>
<td>Concrete</td>
<td>Sunny</td>
<td>Off</td>
<td>25, 35, 45</td>
</tr>
<tr>
<td>SR 331</td>
<td>North</td>
<td>05/18</td>
<td>03.25 – 03.45 pm</td>
<td>Asphalt</td>
<td>Cloudy</td>
<td>Off</td>
<td>25, 35, 44</td>
</tr>
<tr>
<td>SR 331</td>
<td>North</td>
<td>05/18</td>
<td>03.25 – 03.45 pm</td>
<td>Asphalt</td>
<td>Cloudy</td>
<td>On</td>
<td>25, 35, 44</td>
</tr>
<tr>
<td>US 441</td>
<td>North</td>
<td>05/19</td>
<td>10.45 – 11.05 am</td>
<td>Asphalt</td>
<td>Overcast</td>
<td>On</td>
<td>25, 35, 45</td>
</tr>
<tr>
<td>US 441</td>
<td>North</td>
<td>05/19</td>
<td>11.11 – 11.40 am</td>
<td>Asphalt</td>
<td>Overcast</td>
<td>Off</td>
<td>25, 35, 45</td>
</tr>
</tbody>
</table>

To appropriately prepare the selected road sections to be for testing, they had to be temporarily closed for traffic as shown in Figure 4.1(a). First, the longitudinal, transverse, and alligator cracks on selected sections were manually traced on a transparent paper in order to determine the dimensions (length and width) of cracks. Then, the cracks were imaged by a hand-held Minolta DiMage5 3.3-megapixel camera and images were saved as uncompressed TIFF files. Next, two poster boards containing the grayscale and the standard resolution targets (Figure 4.1(b)) were placed in front of the selected crack locations so that the highway evaluation vehicle would pass through and image the targets before imaging the selected cracks. Intensity data obtained from the images of these targets would be used in the study of the effect of noise on images. Each speed was surveyed three times to evaluate the repeatability of the pavement imaging system.
Finally, the FDOT highway evaluation vehicle was driven over the tested area (Figure 4.2 (a)) while capturing the images of the targets and cracks under different lighting, pavement lighting, and speeds conditions indicated in Table 4.1. Each run was repeated three times to account for statistical variations. Subsequently, the data acquired during testing were analyzed to verify the accuracy of the pavement imaging subsystem in recording crack information, based on the following criteria:

1. Identification ability – ability to identify a crack in its entirety, especially with respect to hairline cracks,

2. Crack length – based on the measured lengths of the cracks from the imprint on the transparency and the image. The determination of the length of a crack can be made from the number of pixels forming the image of the crack using software ImageJ,

3. Crack thickness – based on the measured width of the cracks and the computation of the width from the number of pixels corresponding to the crack width in the
image using software *ImageJ*. This determination was limited to easily identifiable locations of the cracks only, and

(4) extent of distortion of the crack – based on the measurement of crack propagation in longitudinal and transverse directions of the image and comparison with the corresponding dimensions based on the imprint on the transparency.

The second phase of the experiment was to determine the distortion in the pavement image due to optics used in the downward imaging system of the FDOT highway evaluation vehicle at different speeds. The relevant testing area was chosen within the FDOT State Materials office complex. A grid of small bright tacks was setup on one location of this site with a relatively new asphalt pavement (Figure 4.2(b)). This 10 inches x 10 inches grid was of square shape where tacks or colored nails were placed at the nodes.

![Figure 4.2](image-url) (a) FDOT Highway Evaluation Vehicle Driven Through the Testing Area; (b) Verification of the Optical Distortion Due to Optics Used in the Pavement Imaging System
4.2 Evaluation of the Noise Due to Speed

The maximum SNR for the Basler L-103 line-scan camera solely due to quantization noise would be 59 dB. Generally, because of the presence of other noise sources, the actual SNR value will be significantly lower than this theoretical one, mainly due to photon noise. One standard way that can be adopted to evaluate the effect of the overall noise on the images captured by the pavement imaging system is to analyze the Signal-to-Noise Ratio (SNR). Therefore, SNR for each testing scenario in Table 4.1 was computed by measuring the intensity values of the images of black and white patches of the resolution target (Figure 4.1(b)). The average SNR value for each individual testing condition was determined and the results are shown in Figures 4.3 to 4.8.

Figure 4.3 SNR and Gain vs. Speed Plot for US 441 with Pavement Lights On
Figure 4.4 SNR and Gain vs. Speed Plot for US 441 with Pavement Lights Off

Figure 4.5 SNR and Gain vs. Speed Plot for SR 331 with Pavement Lights On
Figure 4.6 SNR and Gain vs. Speed Plot for SR 331 with Pavement Lights Off

Figure 4.7 SNR and Gain vs. Speed Plot for SR 28 with Pavement Lights On
Based on Figures 4.3 to 4.8, the maximum and minimum standard deviations of SNR are 1.31 dB and 0.0 dB respectively. The maximum standard deviation of 1.31 dB is observed in the plot in Figure 4.3 probably due to the occurrence of flare in the images due to excessive lighting. Hence, it can be concluded that the SNR does not seem to depend on the speed. The flare effect on the target can also be seen in Figure 3.20(a). In addition, SNR results obtained from SR 28 at a speed of 45 mph without pavement lights were excluded from the results, as at that point, the exposure time of the camera automatically changed from 1/40,000 seconds to 1/19,000 second per each imaging line due to low-lighting conditions. Also, based on the plots presented in Figures 4.3 to 4.8, one can also conclude that the vehicle’s lighting system does introduce a change in SNR due to photon noise and saturation effect of 1 dB for asphalt pavements under cloudy conditions and 10 dB for asphalt pavement for overcast sunny conditions, respectively.
Moreover, the plots also seem to show that the vehicle speed does not contribute to a change in the gain coefficient.

4.3 Evaluation of the Gain Due to Lighting Conditions

Another set of plots presented in Figures 4.9 to 4.15 was generated to show the variation of SNR and gain coefficient (Eqn. (3.2)) for different trials on a given section under a specific lighting condition irrespective of the vehicle speed.

Figure 4.9 Variation of SNR and Gain for US 441 with Pavement Lights On (Exposure 1/40,000 sec)

Figure 4.10 Variation of SNR and Gain for US 441 with Pavement Lights Off (Exposure 1/40,000 sec)
Figure 4.11 Variation of SNR and Gain for SR 331 with Pavement Lights On (Exposure 1/40,000 s)

Figure 4.12 Variation of SNR and Gain for SR 331 with Pavement Lights Off (Exposure 1/40,000 s)
Figure 4.13 Variation of SNR and Gain for SR 28 with Pavement Lights On (Exposure 1/40,000 s)

Figure 4.14 Variation of SNR and Gain for SR 28 with Pavement Lights Off (Exposure 1/40,000 s)
Figure 4.15 Variation of SNR and Gain for SR 28 with Pavement Lights Off (Exposure 1/19,000 s)

The above plots indicate that, when the pavement lighting system is on, the gain coefficient is consistently lowered for both asphalt and concrete pavement under any outside lighting condition (i.e. sunny or cloudy). Moreover, it can be seen that the gain coefficient generally depends not on the pavement type but on the lighting conditions since both asphalt and concrete pavements have similar gain coefficients under sunny conditions either when the pavement lights are turned on (Figure 4.9 and 4.13) or when they are turned off (Figure 4.10 and 4.14). The plots also show that for a given pavement type and outside lighting conditions, the gain coefficients do not vary substantially (standard deviation less than 0.12) with or without the vehicle’s lighting system.

4.4 Evaluation of Pavement Images for Ability to Recognize Cracks

Images captured by the FDOT highway evaluation vehicle were also analyzed to determine the ability of recognition of different crack features. First, the crack features traced on a transparent paper during manual survey (Section 4.1), were used to measure
crack widths and lengths between distinctive points. Then, images of these features captured by the hand-held Minolta DiMage5 3.3-megapixel camera were also evaluated. Next, by using the Equation 2.5, the actual sizes of the same features were computed. Verification of the results of the manual survey was performed by comparing the feature sizes from the manual survey with those computed from the hand-held digital camera. The results of this comparison are shown in Figure 4.16 – 4.25 and Table 4.2 defines the notation used to identify crack features. The error, $\Delta_{dist}$, presented in these figures was computed as:

$$\Delta_{dist} [%] = \left[ \frac{d_{crack} - d'_{crack}}{d_{crack}} \right] 100$$

(4.1)

where $d_{crack}$ and $d'_{crack}$ represent the crack dimensions obtained from the manual survey and that computed from the pavement images captured by the Minolta DiMage5 camera, respectively.
Table 4.2 Definition of Notations Used in Figures 4.16 – 4.25

<table>
<thead>
<tr>
<th>Notation Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>a_DF_1 – a_DF_10</td>
<td>US 441 section, image DF, crack features 1 to 10</td>
</tr>
<tr>
<td>a_DF_vert1 – a_DF_vert3</td>
<td>US 441 section, image DF, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>a_DF_hor1 – a_DF_hor3</td>
<td>US 441 section, image DF, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>a_E_1 – a_E_5</td>
<td>US 441 section, image E, crack features 1 to 5</td>
</tr>
<tr>
<td>a_E_vert1 – a_E_vert3</td>
<td>US 441 section, image E, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>a_E_hor1 – a_E_hor3</td>
<td>US 441 section, image E, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>a_BC_1 – a_BC_3</td>
<td>US 441 section, image BC, crack features 1 to 3</td>
</tr>
<tr>
<td>a_BC_vert1 – a_BC_vert3</td>
<td>US 441 section, image BC, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>a_BC_hor1 – a_BC_hor3</td>
<td>US 441 section, image BC, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>a_A_1 – a_A_3</td>
<td>US 441 section, image A, crack features 1 to 3</td>
</tr>
<tr>
<td>a_A_vert1 – a_A_vert3</td>
<td>US 441 section, image A, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>a_A_hor1 – a_A_hor3</td>
<td>US 441 section, image A, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>b_CD_1 – b_CD_9</td>
<td>SR 331 section, image CD, crack features 1 to 9</td>
</tr>
<tr>
<td>b_CD_vert1 – b_CD_vert3</td>
<td>SR 331 section, image CD, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>b_CD_hor1 – b_CD_hor3</td>
<td>SR 331 section, image CD, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>b_AB_1 – b_AB_4</td>
<td>SR 331 section, image AB, crack features 1 to 4</td>
</tr>
<tr>
<td>b_AB_vert1 – b_AB_vert3</td>
<td>SR 331 section, image AB, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>b_AB_hor1 – b_AB_hor3</td>
<td>SR 331 section, image AB, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>b_EF_1 – b_EF_5</td>
<td>SR 331 section, image EF, crack features 1 to 5</td>
</tr>
<tr>
<td>b_EF_vert1 – b_EF_vert3</td>
<td>SR 331 section, image EF, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>b_EF_hor1 – b_EF_hor3</td>
<td>SR 331 section, image EF, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>c_CE_1 – c_CE_9</td>
<td>SR 28 section, image CE, crack features 1 to 9</td>
</tr>
<tr>
<td>c_CE_vert1 – c_CE_vert3</td>
<td>SR 28 section, image CE, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>c_CE_hor1 – c_CE_hor3</td>
<td>SR 28 section, image CE, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>c_D_1 – c_D_5</td>
<td>SR 28 section, image D, crack features 1 to 5</td>
</tr>
<tr>
<td>c_D_vert1 – c_D_vert3</td>
<td>SR 28 section, image D, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>c_D_hor1 – c_D_hor3</td>
<td>SR 28 section, image D, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>c_AB_1 – c_AB_5</td>
<td>SR 28 section, image AB, crack features 1 to 5</td>
</tr>
<tr>
<td>c_AB_vert1 – c_AB_vert3</td>
<td>SR 28 section, image AB, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>c_AB_hor1 – c_AB_hor3</td>
<td>SR 28 section, image AB, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>f</td>
<td>Focal length set on DiMage 5 camera</td>
</tr>
<tr>
<td>O</td>
<td>Distance from the DiMage 5 lens to the pavement</td>
</tr>
</tbody>
</table>
Figure 4.16 Verification of Manual Survey (US 441, image DF) with Image Captured by DiMage5 Digital Camera

Figure 4.17 Verification of Manual Survey (US 441, image E) with Image Captured by DiMage5 Digital Camera
Figure 4.18 Verification of Manual Survey (US 441, image BC) with Image Captured by DiMage5 Digital Camera

Figure 4.19 Verification of Manual Survey (US 441, image A) with Image Captured by DiMage5 Digital Camera
Figure 4.20 Verification of Manual Survey (SR 331, image CD) with Image Captured by DiMage5 Digital Camera

Figure 4.21 Verification of Manual Survey (SR 331, image AB) with Image Captured by DiMage5 Digital Camera
Figure 4.22 Verification of Manual Survey (SR 331, image EF) with Image Captured by DiMage5 Digital Camera

Figure 4.23 Verification of Manual Survey (SR 28, image CE) with Image Captured by DiMage5 Digital Camera
Figure 4.24 Verification of Manual Survey (SR 28, image D) with Image Captured by DiMage5 Digital Camera

Figure 4.25 Verification of Manual Survey (SR 28, image AB) with Image Captured by DiMage5 Digital Camera
From Figures 4.16 to 4.25 it can be seen that the computed error for features larger than 10 mm is less than 9.6%. It can also be seen that, as feature size decreased, the error generally increases. This is to be expected since a pixel represents a pavement area as large as 2 mm x 2 mm. Therefore, if a hairline crack is of 3 mm width and it is visually estimated as consisting of two pixels, its width is evaluated as 4 mm resulting in an error of 50%. Moreover, the precision of the measurements based on the image was checked by measuring the length of two scales attached to the pavement in longitudinal and transverse directions. Each rectangle printed on these scales has a length of 20 mm. The maximum error arising from the recognition of the scale, measured as an average value from 3 rectangles in each direction, were 0.85 mm or 4.5% \( \left( \frac{0.85 \text{mm}}{20 \text{mm}} \right) \) in the transverse direction and 0.84 or 4.4% \( \left( \frac{0.84 \text{mm}}{20 \text{mm}} \right) \) in the longitudinal direction.

Measurement of crack features in images BC (US 441), EF (SR 331), and AB (SR 28) produced higher errors due to lower precision of the manual survey performed by inexperienced personnel. Considering the above discussed limitations, based on the plots in Figs. 4.16 – 4.25, it can be concluded that the manual survey was reasonably precise.

Based on the manually verified crack widths and lengths, the ability to recognize the same features from images captured by the pavement imaging system was investigated. First, the influence of the speed on the recognition ability was tested and the results are shown in Figures 4.26 to 4.38 and in Tables 4.4 to 4.9. Table 4.3 describes the notation used for identification of crack features. It must be noted that, in these figures,
cracks of zero width or lengths were unrecognizable from the dark images resulting from low-lighting conditions.

### Table 4.3 Definition of Notations Used in Figures 4.26 – 4.39

<table>
<thead>
<tr>
<th>Notation Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_{f1_w, f3_w, f5_w})</td>
<td>US 441 section, image F, width of cracks 1, 3, 5</td>
</tr>
<tr>
<td>(a_{d8_w - d10_w})</td>
<td>US 441 section, image D, width of cracks 8 to 10</td>
</tr>
<tr>
<td>(a_{e1_w, e2_w})</td>
<td>US 441 section, image E, width of cracks 1, 2</td>
</tr>
<tr>
<td>(a_{c1_w, c2_w})</td>
<td>US 441 section, image C, width of cracks 1, 2</td>
</tr>
<tr>
<td>(a_{vert1 - vert3})</td>
<td>US 441 section, image E, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>(a_{hor1 - hor3})</td>
<td>US 441 section, image E, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>(a_{e3_t, e5_t})</td>
<td>US 441 section, image E, length of cracks 3, 5</td>
</tr>
<tr>
<td>(b_{c1_w, c2_w})</td>
<td>SR 331 section, image C, width of cracks 1, 2</td>
</tr>
<tr>
<td>(b_{d9_w})</td>
<td>SR 331 section, image D, width of crack 9</td>
</tr>
<tr>
<td>(b_{e2_w})</td>
<td>SR 331 section, image E, width of crack 2</td>
</tr>
<tr>
<td>(b_{f3_w, f5_w})</td>
<td>SR 331 section, image C, width of cracks 3, 5</td>
</tr>
<tr>
<td>(b_{vert1 - vert3})</td>
<td>SR 331 section, image C, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>(b_{hor1 - hor3})</td>
<td>SR 331 section, image C, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>(b_{c3_t, c4_t, c8_t})</td>
<td>SR 331 section, image C, length of cracks 3, 4, 8</td>
</tr>
<tr>
<td>(b_{a1_t})</td>
<td>SR 331 section, image A, length of crack 1</td>
</tr>
<tr>
<td>(b_{b2_t, b3_t})</td>
<td>SR 331 section, image B, length of cracks 2, 3</td>
</tr>
<tr>
<td>(c_{d1_w - d3_w, d5_w})</td>
<td>SR 28 section, image D, width of cracks 3, 4, 8</td>
</tr>
<tr>
<td>(c_{e3_w - e5_w, e7_w - e9_w})</td>
<td>SR 28 section, image C, width of cracks 3 – 5, 7 – 9</td>
</tr>
<tr>
<td>(c_{a1_w, a2_w, a4_w})</td>
<td>SR 28 section, image A, width of cracks 1, 2, 4</td>
</tr>
<tr>
<td>(c_{vert1 - vert3})</td>
<td>SR 28 section, image C, scale in transverse direction, rectangles 1 to 3</td>
</tr>
<tr>
<td>(c_{hor1 - hor3})</td>
<td>SR 28 section, image C, scale in longitudinal direction, rectangles 1 to 3</td>
</tr>
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</table>
Figure 4.26 Widths of the Crack Features (US 441, lights on) Measured from Images at Different Speeds

Figure 4.27 Lengths of the Crack Features (US 441, lights on) Measured from Images at Different Speeds
Figure 4.28 Widths of the Crack Features (US 441, lights off) Measured from Images at Different Speeds
Figure 4.29 Lengths of the Crack Features (US 441, lights off) Measured from Images Captured at Different Speeds

Figure 4.30 Widths of the Crack Features (SR 331, lights on) Measured from Images at Different Speeds

Figure 4.31 Lengths of the Crack Features (SR 331, lights on) Measured from Images at Different Speeds
Figure 4.32 Widths of the Crack Features (SR 331, lights off) Measured from Images at Different Speeds

Figure 4.33 Lengths of the Crack Features (SR 331, lights off) Measured from Images at Different Speeds
Figure 4.34 Widths of the Crack Features (SR 28, lights on) Measured from Images at Different Speeds

Figure 4.35 Lengths of the Crack Features (SR 28, lights on) Measured from Images at Different Speeds
Figure 4.36 Widths of the Crack Features (SR 28, lights off) Measured from Images at Different Speeds

Figure 4.37 Lengths of the Crack Features (SR 28, lights off) Measured from Images at Different Speeds
Table 4.4 Dimensions of Crack Features Evaluated Based on the Images and the Corresponding Errors (Δ) at Different Speeds (US 441, lights on)

<table>
<thead>
<tr>
<th>Feature</th>
<th>Measured Dimension [mm]</th>
<th>Dimension/Std. Dev. 25 mph [mm]</th>
<th>Δ 25 mph [%]</th>
<th>Dimension/Std. Dev. 35 mph [mm]</th>
<th>Δ 35 mph [%]</th>
<th>Dimension/Std. Dev. 45 mph [mm]</th>
<th>Δ 45 mph [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>a_f1_w</td>
<td>16.5</td>
<td>17.3 / 1.44</td>
<td>4.9</td>
<td>19.9 / 2.72</td>
<td>20.7</td>
<td>17.1 / 2.76</td>
<td>13.6</td>
</tr>
<tr>
<td>a_f3_w</td>
<td>4.0</td>
<td>5.8 / 1.91</td>
<td>45.4</td>
<td>5.7 / 1.76</td>
<td>42.7</td>
<td>6.3 / 1.09</td>
<td>57.5</td>
</tr>
<tr>
<td>a_f5_w</td>
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<td>5.1 / 0.90</td>
<td>103.2</td>
<td>4.4 / 1.09</td>
<td>76.4</td>
<td>1.9 / 0.00</td>
<td>24.4</td>
</tr>
<tr>
<td>a_vert1</td>
<td>20.0</td>
<td>18.3 / 1.09</td>
<td>8.7</td>
<td>17.0 / 0.00</td>
<td>15.0</td>
<td>17.6 / 1.09</td>
<td>11.8</td>
</tr>
<tr>
<td>a_vert2</td>
<td>20.0</td>
<td>18.3 / 1.09</td>
<td>8.7</td>
<td>17.0 / 0.00</td>
<td>15.0</td>
<td>17.0 / 0.07</td>
<td>14.8</td>
</tr>
<tr>
<td>a_vert3</td>
<td>20.0</td>
<td>17.0 / 0.00</td>
<td>15.0</td>
<td>17.0 / 1.89</td>
<td>15.0</td>
<td>17.6 / 1.09</td>
<td>11.8</td>
</tr>
<tr>
<td>a_hor1</td>
<td>20.0</td>
<td>22.7 / 0.00</td>
<td>13.4</td>
<td>22.7 / 0.00</td>
<td>13.4</td>
<td>22.1 / 1.04</td>
<td>10.4</td>
</tr>
<tr>
<td>a_hor2</td>
<td>20.0</td>
<td>22.7 / 0.00</td>
<td>13.4</td>
<td>20.8 / 1.89</td>
<td>3.9</td>
<td>21.4 / 1.09</td>
<td>7.1</td>
</tr>
<tr>
<td>a_hor3</td>
<td>20.0</td>
<td>22.0 / 1.09</td>
<td>10.2</td>
<td>22.0 / 1.09</td>
<td>10.2</td>
<td>22.0 / 1.09</td>
<td>10.2</td>
</tr>
<tr>
<td>a_d8_w</td>
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<td>7.7 / 0.85</td>
<td>14.2</td>
<td>9.6 / 0.85</td>
<td>7.2</td>
<td>6.9 / 0.65</td>
<td>23.8</td>
</tr>
<tr>
<td>a_d9_w</td>
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<td>18.0 / 1.72</td>
<td>2.4</td>
<td>18.4 / 2.66</td>
<td>0.7</td>
<td>16.8 / 1.32</td>
<td>9.4</td>
</tr>
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<td>4.2 / 0.55</td>
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<td>5.5</td>
<td>13.5 / 0.26</td>
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<td>12.3 / 0.96</td>
<td>5.3</td>
</tr>
<tr>
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<td>15.5 / 2.62</td>
<td>3.5</td>
<td>14.5 / 3.64</td>
<td>3.0</td>
<td>11.3 / 1.34</td>
<td>24.8</td>
</tr>
<tr>
<td>a_e3_t</td>
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<td>148.8 / 4.28</td>
<td>5.3</td>
<td>143.7 / 2.70</td>
<td>8.5</td>
<td>143.1 / 6.58</td>
<td>8.9</td>
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<tr>
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<td>178.0 / 17.2</td>
<td>5.9</td>
<td>185.8 / 1.64</td>
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<td>173.6 / 7.47</td>
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<td>8.2 / 1.09</td>
<td>36.5</td>
<td>5.0 / 1.09</td>
<td>16.0</td>
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</tbody>
</table>

Table 4.5 Dimensions of Crack Features Evaluated Based on the Images and the Corresponding Errors (Δ) at Different Speeds (US 441, lights off)

<table>
<thead>
<tr>
<th>Feature</th>
<th>Measured Dimension [mm]</th>
<th>Dimension/Std. Dev. 25 mph [mm]</th>
<th>Δ 25 mph [%]</th>
<th>Dimension/Std. Dev. 35 mph [mm]</th>
<th>Δ 35 mph [%]</th>
<th>Dimension/Std. Dev. 45 mph [mm]</th>
<th>Δ 45 mph [%]</th>
</tr>
</thead>
<tbody>
<tr>
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<td>16.5</td>
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<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>a_f3_w</td>
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<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>a_f5_w</td>
<td>2.5</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>a_vert1</td>
<td>20.0</td>
<td>17.6 / 1.09</td>
<td>11.8</td>
<td>17.6 / 1.09</td>
<td>11.8</td>
<td>18.3 / 1.09</td>
<td>8.7</td>
</tr>
<tr>
<td>a_vert2</td>
<td>20.0</td>
<td>17.0 / 0.00</td>
<td>15.0</td>
<td>17.6 / 2.18</td>
<td>11.8</td>
<td>16.4 / 1.09</td>
<td>8.1</td>
</tr>
<tr>
<td>a_vert3</td>
<td>20.0</td>
<td>18.9 / 0.00</td>
<td>5.5</td>
<td>17.6 / 2.18</td>
<td>11.8</td>
<td>18.9 / 0.00</td>
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<tr>
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<td>20.0</td>
<td>22.0 / 1.09</td>
<td>10.2</td>
<td>23.6 / 0.95</td>
<td>17.8</td>
<td>22.7 / 1.89</td>
<td>13.4</td>
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<tr>
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<td>22.0 / 1.09</td>
<td>10.2</td>
<td>22.0 / 1.09</td>
<td>10.2</td>
<td>21.4 / 1.09</td>
<td>7.1</td>
</tr>
<tr>
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<td>22.0 / 1.09</td>
<td>10.2</td>
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<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
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<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
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<td>Not visible n/a</td>
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<td>Not visible n/a</td>
<td>n/a</td>
</tr>
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<td>28.6</td>
<td>8.6 / 0.95</td>
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<td>6.4 / 1.27</td>
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<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
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<td>a_e5_t</td>
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<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>a_c1_w</td>
<td>16.0</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>a_c2_w</td>
<td>6.0</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
<td>n/a</td>
<td>Not visible n/a</td>
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Table 4.6 Dimensions of Crack Features Evaluated Based on the Images and the Corresponding Errors ($\Delta$) at Different Speeds (SR 331, lights on)

<table>
<thead>
<tr>
<th>Feature</th>
<th>Measured Dimension [mm]</th>
<th>Dimension/Std. Dev. 25 mph [mm]</th>
<th>$\Delta$ Dimension/25 mph [%]</th>
<th>Dimension/Std. Dev. 35 mph [mm]</th>
<th>$\Delta$ Dimension/35 mph [%]</th>
<th>Dimension/Std. Dev. 45 mph [mm]</th>
<th>$\Delta$ Dimension/45 mph [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>b_c1_w</td>
<td>3.2</td>
<td>3.8 / 1.89</td>
<td>18.1</td>
<td>4.8 / 1.19</td>
<td>50.6</td>
<td>4.3 / 0.45</td>
<td>34.4</td>
</tr>
<tr>
<td>b_c2_w</td>
<td>11.0</td>
<td>15.2 / 3.83</td>
<td>38.1</td>
<td>14.9 / 0.95</td>
<td>35.6</td>
<td>11.5 / 0.00</td>
<td>4.8</td>
</tr>
<tr>
<td>b_c3 t</td>
<td>9.0</td>
<td>11.4 / 2.34</td>
<td>26.6</td>
<td>12.6 / 2.32</td>
<td>39.8</td>
<td>10.0 / 2.84</td>
<td>11.3</td>
</tr>
<tr>
<td>b_vert1</td>
<td>20.0</td>
<td>17.0 / -</td>
<td>15.0</td>
<td>Not visible</td>
<td>n/a</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_vert2</td>
<td>20.0</td>
<td>15.1 / -</td>
<td>24.4</td>
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<td>n/a</td>
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<td>n/a</td>
</tr>
<tr>
<td>b_vert3</td>
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<td>17.0 / -</td>
<td>15.0</td>
<td>Not visible</td>
<td>n/a</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_hor1</td>
<td>20.0</td>
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<td>0.8</td>
<td>Not visible</td>
<td>n/a</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_hor2</td>
<td>20.0</td>
<td>19.5 / 2.18</td>
<td>2.4</td>
<td>Not visible</td>
<td>n/a</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
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<td>19.8 / 1.34</td>
<td>0.8</td>
<td>Not visible</td>
<td>n/a</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_c4 t</td>
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<td>10.1 / 2.89</td>
<td>26.0</td>
<td>12.0 / 1.09</td>
<td>49.6</td>
<td>13.3 / 0.09</td>
<td>66.0</td>
</tr>
<tr>
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<td>13.0 / 0.96</td>
<td>8.2</td>
<td>14.2 / 2.30</td>
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<td>14.2 / 0.33</td>
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<td>19.0</td>
<td>10.2 / 1.14</td>
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<td>26.6 / 1.67</td>
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<td>30.9 / 3.87</td>
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<td>33.7 / 6.79</td>
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<td>29.9 / 1.44</td>
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<td>59.5 / 12.83</td>
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<td>70.4 / 1.91</td>
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<td>6.2 / 1.65</td>
<td>12.4</td>
<td>7.8 / 1.95</td>
<td>40.9</td>
<td>6.0 / 1.34</td>
<td>8.6</td>
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Table 4.7 Dimensions of Crack Features Evaluated Based on the Images and the Corresponding Errors ($\Delta$) at Different Speeds (SR 331, lights off)

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<tr>
<th>Feature</th>
<th>Measured Dimension [mm]</th>
<th>Dimension/Std. Dev. 25 mph [mm]</th>
<th>$\Delta$ Dimension/25 mph [%]</th>
<th>Dimension/Std. Dev. 35 mph [mm]</th>
<th>$\Delta$ Dimension/35 mph [%]</th>
<th>Dimension/Std. Dev. 45 mph [mm]</th>
<th>$\Delta$ Dimension/45 mph [%]</th>
</tr>
</thead>
<tbody>
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<td>6.1 / 0.00</td>
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<td>3.8 / -</td>
<td>18.1</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_c2_w</td>
<td>11.0</td>
<td>13.1 / 0.23</td>
<td>18.8</td>
<td>13.8 / -</td>
<td>25.8</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_c3 t</td>
<td>9.0</td>
<td>15.9 / 0.99</td>
<td>77.2</td>
<td>14.0 / -</td>
<td>55.4</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_vert1</td>
<td>20.0</td>
<td>17.0 / 0.00</td>
<td>15.0</td>
<td>17.0 / -</td>
<td>15.0</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_vert2</td>
<td>20.0</td>
<td>17.0 / 0.00</td>
<td>15.0</td>
<td>15.1 / -</td>
<td>24.4</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_vert3</td>
<td>20.0</td>
<td>17.0 / 0.00</td>
<td>15.0</td>
<td>17.0 / -</td>
<td>15.0</td>
<td>Not visible</td>
<td>n/a</td>
</tr>
<tr>
<td>b_hor1</td>
<td>20.0</td>
<td>20.2 / 1.03</td>
<td>1.0</td>
<td>21.7 / 1.34</td>
<td>8.7</td>
<td>20.8 / -</td>
<td>3.9</td>
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<td>20.2 / 2.89</td>
<td>0.8</td>
<td>20.8 / 0.00</td>
<td>3.9</td>
<td>18.9 / -</td>
<td>5.5</td>
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<td>20.8 / 3.27</td>
<td>3.9</td>
<td>21.7 / 1.34</td>
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<td>20.8 / -</td>
<td>3.9</td>
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<td>13.4 / 0.00</td>
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<td>1.0</td>
<td>11.5 / -</td>
<td>4.0</td>
<td>Not visible</td>
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</tr>
<tr>
<td>b_d9 w</td>
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<td>16.1 / 4.53</td>
<td>79.0</td>
<td>12.1 / -</td>
<td>34.1</td>
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<td>n/a</td>
</tr>
<tr>
<td>b_a1 t</td>
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<td>36.0 / 0.00</td>
<td>25.7</td>
<td>41.5 / 2.65</td>
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<td>n/a</td>
</tr>
<tr>
<td>b_b2 t</td>
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<td>43.7 / 8.29</td>
<td>39.6</td>
<td>40.3 / 8.10</td>
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<td>40.5 / 23.83</td>
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<tr>
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<td>67.8 / 1.41</td>
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<td>70.6 / 3.36</td>
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<tr>
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<td>2.8 / 1.34</td>
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<td>4.6 / -</td>
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<tr>
<td>b_f3 w</td>
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<td>4.9 / 1.65</td>
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<td>7.9 / -</td>
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<tr>
<td>b_f5 w</td>
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<td>4.2 / 0.55</td>
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<td>1.9 / -</td>
<td>65.6</td>
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Table 4.8 Dimensions of Crack Features Evaluated Based on the Images and the Corresponding Errors (Δ) at Different Speeds (SR 28, lights on)

<table>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
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<td>c_d1_w</td>
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<td>7.1/0.89</td>
<td>1.0</td>
<td>6.1/0.00</td>
<td>12.6</td>
<td>6.1/0.00</td>
<td>12.6</td>
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<td>7.8/0.18</td>
<td>0.5</td>
<td>7.3/1.01</td>
<td>6.6</td>
<td>6.6/0.83</td>
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<td>Not visible</td>
<td>n/a</td>
<td>1.9/-</td>
<td>214.9</td>
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<td>11.8</td>
<td>18.3/1.09</td>
<td>8.7</td>
<td>17.0/0.00</td>
<td>15.0</td>
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<td>17.0/0.00</td>
<td>15.0</td>
<td>17.0/0.00</td>
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<td>17.0/0.00</td>
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<td>15.0</td>
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<td>21.4/1.09</td>
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<td>20.8/1.09</td>
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<td>2.5/1.09</td>
<td>151.9</td>
<td>2.5/1.09</td>
<td>151.9</td>
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<td>89.0</td>
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<td>Not visible</td>
<td>n/a</td>
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<td>6.7/1.01</td>
<td>34.0</td>
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<td>6.5/0.65</td>
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<td>22.7/0.95</td>
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Table 4.9 Dimensions of Crack Features Evaluated Based on the Images and the Corresponding Errors (Δ) at Different Speeds (SR 28, lights off)

<table>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>c_d1_w</td>
<td>7.0</td>
<td>6.1/0.00</td>
<td>12.6</td>
<td>6.7/1.01</td>
<td>4.3</td>
<td>6.1/0.00</td>
<td>12.6</td>
</tr>
<tr>
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<td>8.4/1.15</td>
<td>7.3</td>
<td>8.2/1.84</td>
<td>4.7</td>
<td>8.7/0.91</td>
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<td>214.9</td>
<td>3.8/-</td>
<td>529.9</td>
<td>3.8/-</td>
<td>529.9</td>
</tr>
<tr>
<td>c_d5_w</td>
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<td>4.4/1.09</td>
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<td>Not visible</td>
<td>n/a</td>
<td>3.8/1.89</td>
<td>190.7</td>
</tr>
<tr>
<td>c_vert1</td>
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<td>17.6/1.09</td>
<td>11.8</td>
<td>17.6/1.09</td>
<td>11.8</td>
<td>17.0/0.00</td>
<td>15.0</td>
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<tr>
<td>c_vert2</td>
<td>20.0</td>
<td>17.0/0.00</td>
<td>15.0</td>
<td>17.6/1.09</td>
<td>11.8</td>
<td>17.0/0.00</td>
<td>15.0</td>
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<td>17.7/1.06</td>
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<td>17.6/1.09</td>
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<td>17.0/0.00</td>
<td>15.0</td>
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<td>c_hor1</td>
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<td>22.7/0.00</td>
<td>13.4</td>
<td>22.0/1.09</td>
<td>10.2</td>
<td>22.7/0.00</td>
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<tr>
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<td>21.4/1.09</td>
<td>7.1</td>
<td>20.8/0.00</td>
<td>3.9</td>
<td>21.7/1.34</td>
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<td>22.7/0.00</td>
<td>13.4</td>
<td>21.4/1.09</td>
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<td>539.4</td>
<td>4.6/-</td>
<td>470.2</td>
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<td>2.8/1.34</td>
<td>183.4</td>
<td>5.7/-</td>
<td>466.9</td>
<td>3.8/1.89</td>
<td>277.9</td>
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<td>5.1/0.90</td>
<td>27.0</td>
<td>7.0/1.49</td>
<td>74.4</td>
<td>6.5/2.09</td>
<td>61.5</td>
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<td>2.8/1.54</td>
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<td>3.7/1.54</td>
<td>267.1</td>
<td>4.0/1.94</td>
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<td>169.9</td>
<td>3.8/-</td>
<td>439.9</td>
<td>1.9/0.00</td>
<td>169.9</td>
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<tr>
<td>c_a1_w</td>
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<td>6.1/0.00</td>
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<td>7.4/0.36</td>
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<td>24.8/1.24</td>
<td>18.2</td>
<td>23.2/1.64</td>
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</table>
Based on Figures 4.26 to 4.37, it can be concluded that the vehicle speed does not play a significant role in the recognition ability of crack widths and lengths. When the vehicle lighting system is on, the largest difference between widths estimated at different speeds is 3.2 mm (Figure 4.26) for overcast sunny conditions and crack widths less than 10 mm. Similarly, when the vehicle lighting system is off, the largest difference between widths estimated at different speeds is 3.1 mm (Figure 4.28) for overcast sunny conditions and crack widths less than 10 mm. Hence it can be concluded that overcast sunny conditions create an environment the pavement imaging system has most problems with and introduces a higher uncertainty into the recognition of the crack features. The above figures also show that for asphalt pavements the error of recognition with the lighting system is lower than when it is off. Moreover, without the lighting system there were a number of situations where it was unable to recognize pavement features. For concrete pavements on the other hand the recognition ability was not an issue. The error with the lighting system was smaller than that without it. Based on the results in Tables 4.4 to 4.9, conclusions regarding the repeatability of image based crack feature evaluation are presented in Table 4.10. Table 4.10 depicts the maximum and minimum standard deviations involved in crack feature evaluation based on images at any speed.
Table 4.10 Repeatability of Crack Evaluation

<table>
<thead>
<tr>
<th>Feature Size – Lighting System</th>
<th>Standard Deviation of Crack Evaluation (Max/Min)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>US 441 (asphalt)</td>
</tr>
<tr>
<td>(&lt; 3 mm) – on</td>
<td>1.09 / 0.00</td>
</tr>
<tr>
<td>(&lt; 3 mm) – off</td>
<td>Not Visible</td>
</tr>
<tr>
<td>(3 – 6 mm) – on</td>
<td>3.09 / 0.55</td>
</tr>
<tr>
<td>(3 – 6 mm) – off</td>
<td>Not Visible</td>
</tr>
<tr>
<td>(&gt; 6 mm) – on</td>
<td>17.2 / 0.00</td>
</tr>
<tr>
<td>(&gt; 6 mm) – off</td>
<td>Not Visible / 0.00</td>
</tr>
</tbody>
</table>

In the next step, the images were evaluated to investigate any possible correlation between the SNR values presented in plots in Figures 4.3 to 4.8 and error associated with the evaluation of crack width and length shown in Figures 4.26 to 4.37. Based on Figures 4.38 and 4.39, one can see that when the SNR value is relatively high, error associated with the measured widths or lengths of crack features generally reduces. Only the plots where the difference between maximum and minimum SNR value is more than 1 dB are used to generate Figures 4.38 and 4.39.
Figure 4.38 Correlation Between Variability in Crack Measurements and SNR Values for US 441

Figure 4.39 Correlation Between Variability in Crack Measurements and SNR Values for SR 28
4.5 Evaluation of the Effect of the Vehicle Movement on Image

Inertial data produced by the IMU unit are integrated by the POS computer in the FDOT highway evaluation vehicle to evaluate data relevant to roadway geometry. Therefore, even with the time interval corresponding to one image frame, one can extract the data relevant from the IMU, such as velocities in the $x$, $y$, and $z$ directions in the global coordinate system and accelerations in the $x$, $y$, and $z$ directions of the body coordinate system. These raw data were processed through the *Applanix POSPack* program shown in Figure 4.40.

Then, the velocities in the global coordinate system ($v_{global_x}$, $v_{global_y}$, $v_{global_z}$) were transformed into the corresponding velocities in the body coordinate system ($v_{body_x}$, $v_{body_y}$) using following equations:

$$v_{body_x} = v_{global_x} \cos(\alpha) + v_{global_y} \sin(\alpha)$$  \hspace{1cm} (4.2)

$$v_{body_y} = v_{global_x} \cos(\alpha) - v_{global_y} \sin(\alpha)$$  \hspace{1cm} (4.3)

$$v_{body_z} \approx v_{global_z} \cos(\theta)$$  \hspace{1cm} (4.4)

where $\alpha$ is the heading and $\theta$ represents the roll or cross-slope.

Figure 4.40 Global vs. Body Coordinate System
Next, the incremental distances (\( \Delta \)) traveled by the vehicle in the x, y, and z directions of the body coordinate system were computed from the corresponding velocities (\( v_{body_i} \)) and accelerations (\( a_{body_i} \)) as:

\[
\Delta = \frac{v_{body_i} + v_{body_{i+1}}}{2} (t_{i+1} - t_i) = \frac{v_{body_i} + \left( a_{body_i} + \frac{a_{body_{i+1}}}{2} \right) (t_{i+1} - t_i)}{2} (t_{i+1} - t_i) \tag{4.5}
\]

where \((t_{i+1} - t_i)\) is the considered time interval equal to 0.05 second.

For the testing run on US 441, acceleration and velocity results for testing duration (time interval of 312,297.2524 – 312,313.6973) are shown in Figures 4.41 and 4.42. The distances computed using Eqn. (4.5) are plotted in Figures 4.43 to 4.45 and 4.46 to 4.48 for US441 and SR 331, respectively.
Figure 4.42 Body Acceleration Data on US 441

Figure 4.43 Body Velocity Data in the X Direction on US 441
Figure 4.44 Incremental Distance Traveled in the X Direction on US 441

Figure 4.45 Incremental Distance Traveled in the Y Direction on US 441
Figure 4.46 Incremental Distance Traveled in the Z Direction on US 441

Figure 4.47 Incremental Distance Traveled in the X Direction on SR 331
Figure 4.48 Incremental Distance Traveled in the Y Direction on SR 331

Figure 4.49 Incremental Distance Traveled in the Z Direction on SR 331
Maximum and average distance values, representing the displacement of the vehicle in a period of 0.05 s corresponding to the IMU’s collection data frequency of 1/200 Hz, were extracted from Figures 4.44 to 4.48. Then the simple lens formula (Eqn. (2.3)) was used to determine the movement of the pavement features on the sensor in the three directions x, y, and z as:

\[
d_{sensor, x} = \left[ \frac{f}{(O + f)} \right] d_{object, x} \tag{4.6}
\]

\[
d_{sensor, y} = \left[ \frac{f}{(O + f)} \right] d_{object, y} \tag{4.7}
\]

\[
d_{sensor, z} = \left[ \frac{f}{(O + f + d_{object, z})} \right] - \left[ \frac{f}{(O + f)} \right] \tag{for a unit size} \tag{4.8}
\]

Then, the displacement in pixels, \( \Delta_{sensor} \), in the x, y, or z direction can be computed as:

\[
\Delta_{sensor} = \frac{d_{sensor}}{p} \tag{4.9}
\]

where \( d_{sensor} \) represents distance change on the sensor due to the movement of the vehicle in x, y, or z directions and \( p \) is pixel pitch of the Basler L103 line-scan camera.

The complete results of this evaluation are presented in Table 4.10. Based on the results for a speed of 25 mph, it can be concluded that the vertical (z) movement of the vehicle for exposure times of 1/19,000 or 1/40,000 seconds does not introduce any error. In the x and y directions, the movement of vehicle does not introduce any substantial error except in the x direction on both US 441 and SR 331 where an exposure time of 1/19,000 seconds was used. The magnitude of this error is approximately 32% and close
to the Nyquist frequency limit. For highway speed and exposure time of 1/19,000
seconds, the movement of vehicle in the $x$ direction can become a limiting factor in image
quality evaluation.

Table 4.11 Number of Pixels in Image Displacement Due to Vehicle Movement (25 mph)

<table>
<thead>
<tr>
<th>Road Name</th>
<th>Body Coordinates</th>
<th>Avg Distance traveled [mm] in 1/200 s</th>
<th>Max Distance traveled [mm] in 1/200 s</th>
<th>Avg Displacement of image in pixels in 1/19,000 s</th>
<th>Max Displacement of image in pixels in 1/19,000 s</th>
<th>Avg Displacement of image in pixels in 1/40,000 s</th>
<th>Max Displacement of image in pixels in 1/40,000 s</th>
</tr>
</thead>
<tbody>
<tr>
<td>US 441</td>
<td>$x$</td>
<td>56.0</td>
<td>57.0</td>
<td>0.32</td>
<td>0.31</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>$y$</td>
<td>0.7</td>
<td>2.5</td>
<td>0.014</td>
<td>0.004</td>
<td>0.007</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>$z$</td>
<td>1.0</td>
<td>4.5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>SR 331</td>
<td>$x$</td>
<td>54.0</td>
<td>57.0</td>
<td>0.32</td>
<td>0.30</td>
<td>0.15</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>$y$</td>
<td>0.2</td>
<td>1.2</td>
<td>0.007</td>
<td>0.001</td>
<td>0.003</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>$z$</td>
<td>0.5</td>
<td>1.25</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
CHAPTER 5

CONCLUSION

Guidelines for the objective assessment of imaging systems are presented in this dissertation for the benefit of agencies that use imaging systems to conduct periodic monitoring of pavement, traffic, and safety features. The dissertation also describes how the above guidelines can be used to identify the appropriate settings of the imaging systems and the most favorable imaging conditions which would improve the efficiency and reliability of infrastructure monitoring operations. The guidelines were developed based on the assessment of the Florida Department of Transportation (FDOT) highway evaluation vehicle’s imaging system components; forward-view and side-view digital area-scan cameras as well as the digital line-scan pavement camera.

The spatial resolution tests were used to determine the relationships among assessment parameters such as the minimum identifiable size of relevant features and the contrast and optical settings such as the focal length, exposure time and the distance of view. These findings will enable the user to set the field of view of evaluation cameras depending on their optical characteristics and the evaluation needs. As for the highway feature imaging system of the FDOT highway evaluation vehicle, the optimum aperture settings were determined based on the maximum dynamic range criterion. A key adjustment that influences the color quality of images is the white balance and this study revealed that it can be effectively achieved by the evaluation of color resolution. The
results of the study further indicate the need for repeating white balancing if lighting conditions vary significantly during the imaging operation. In routine monitoring operations, the creation of a number of preset white balance initialization files that correspond to different lighting conditions would certainly expedite the evaluation process. Assessment of color resolution was also shown to be helpful in determining the optimum aperture settings and the effectiveness of filters in upgrading the quality of images.

The study also indicated how the signal-to-noise ratio represents another criterion for the selection of aperture setting and the optimum lighting conditions. In addition, the noise effects due to vehicular vibration were quantified in terms of the degree of image displacement as a prelude to development of criteria for overcoming blurring in images. Also, the noise evaluation provides a methodical means of assessing the effectiveness of techniques that can be utilized to mitigate the effects of vibration such as rubber shock-absorption casings and reduced exposure times. Useful relationships were also formulated to quantify the effects of exposure times and vehicle speed on the clarity of images. To quantify the degree of distortion induced by imaging systems and to identify improved optics such as aspherical lenses that can minimize the distortion effects, standard distortion evaluation methods were presented.

It is common for some transportation agencies to out-source the imaging operations and other evaluations while other agencies adopt in-house operations and evaluations. The image quality assessment guidelines presented in this dissertation will furnish definitive criteria for specification of the resolution expectations of the
outsourcing agency to the vendors. Furthermore, in the case of in-house evaluators, these guidelines will provide objective criteria to assess the capabilities and limitations of their imaging systems and the impact of operating conditions such as illumination, vehicle speed, road roughness etc. on the image quality. In fact, these criteria can in turn be used in identifying the appropriate operating conditions that will mitigate the undesirable effects.

Common imaging issues of distortion, lack of sharpness, etc. are generally resolved with improved optics. However, the eventual performance of such newly introduced optical system components within a broad imaging system, that also contains capturing and post-processing software, cannot be predicted from the manufacturers’ specifications alone. In this respect, the protocol laid out in this dissertation for maximizing the efficiency of imaging operations will be useful in assessing the effectiveness of optical sub-systems when they become integral parts of an imaging system. On the other hand, issues concerning appropriate settings will have to be resolved by the users themselves. As such, the assessment methods hereby discussed will furnish convenient tools to achieve white balance and optimum aperture, exposure, and gain settings.

Finally, an experimental investigation was conducted to study the effect of the vehicle speed, pavement type, and different lighting conditions on the pavement images captured with the digital line-scan imaging system. It showed that the vehicle speed does not significantly affect the noise in the images, the camera gain settings, and the ability of recognition of cracks in a pavement. Moreover, the research findings show that
conditions that produce relatively higher SNR in fact improve the accuracy of crack evaluation. The study also shows that the lighting system introduces a significant level of noise into the images while reducing the gain in both asphalt and concrete pavements. Crack measurements are seen to have a higher variability in surveys with the pavement lighting system turned off due to the higher uncertainty in crack recognition. Based on the research findings, it can be concluded that for hairline cracks with a thickness less than 5 mm, the error in recognition ability is relatively high, sometimes reaching over 100%. On the other hand, for features larger than 10 mm in width or length, the above error is less than 9.6%.

The frontier of imaging technology lies in the development of software that can be used to accurately classify and quantify pavement distress on a real-time basis. Such automation efforts would indeed be boosted by the knowledge gained from this research in general and the adoption of the presented assessment techniques in particular since they provide the tools to determine the tonal and spatial resolution limitations of imaging systems and means of enhancing accurate imaging capabilities.
REFERENCES


<http://www.techtv.com/screensavers/print/0,23102,1298,00.html>.


BIBLIOGRAPHY


Appendix A: Sample Report for MTF Evaluation Using PhotoES_AM Plugin for ImageJ

MTF from HOR or VERT visual resolution bars (6-20)
-----------------------------------------------------------
Vert. size of the sensor: 5.32 mm
Horiz size of the sensor: 7.18 mm
Vert. number of pixels on sensor: 1546.0 pixels
Hori. number of pixels on sensor: 2048.0 pixels
Nyquist Frequency: 143.10 lp/mm

Pixel Size/Spacing (ideal square): 3.5 microMeters
Scale (frequency): 12 (112.8 lp/mm)
Comput frequency: 115.2 lp/mm
Error in frequency: 2.1 %

The ave luminance for the black areas: 29.0
The ave luminance for the white areas: 155.0
Low frequency (black-white) contrast C(0): 0.70
Contrast at spatial frequency C(112.8 lp/mm): 0.01
MTF(112.8 lp/mm): 4.1 %
CTF(112.8 lp/mm): 5.3 %
---------------------------------------

MTF from HOR or VERT visual resolution bars (6-20)
-----------------------------------------------------------
Measurement No: 60
Starting point X: 214
Starting point Y: 15
Lenght of LINE: 0.96

** ERROR: System could not recognize black - white - black - white - ... - black pattern **
** WARNING: System could not recognize whole pattern (before column 39.0) **
** ADVICE: Please try to use lower frequency

Vert. size of the sensor: 5.32 mm
Horiz size of the sensor: 7.18 mm
Vert. number of pixels on sensor: 1546.0 pixels
Hori. number of pixels on sensor: 2048.0 pixels
Nyquist Frequency: 143.10 lp/mm

Pixel Size/Spacing (ideal square): 3.5 microMeters
Scale (frequency): 13 (122.2 lp/mm)
Comput frequency: 115.2 lp/mm
Error in frequency: 5.7 %

The ave luminance for the black areas: 24.0
The ave luminance for the white areas: 156.0
Low frequency (black-white) contrast C(0): 0.71
Contrast at spatial frequency C(122.2 lp/mm): 0.00
MTF(122.2 lp/mm): 0.9 %
CTF(122.2 lp/mm): 0.6 %
---------------------------------------
Appendix B: Sample Report for SNR Evaluation Using PhotoES_AM Plugin for ImageJ

| Creating File: SNRtesting_compass_BMP_15percentGaussNoise |

SIGNAL TO NOISE RATIO (MacBeth Target)

Measurement No: -5
Width: 11 pixels
Height: 334 pixels
Node coordinate X: 542 pixels
Node coordinate Y: 102 pixels

Average Black value: 42.0
Average White value: 130.0
Standard Deviation (for active ROI): 11.432
Pixel Count: 3674

Black SNR: 7.6 (17.7 dB)
Black SNR area: 466.4

SIGNAL TO NOISE RATIO (MacBeth Target)

Measurement No: -4
Width: 91 pixels
Height: 93 pixels
Node coordinate X: 340 pixels
Node coordinate Y: 171 pixels

Average Black value: 42.0
Average White value: 130.0
Standard Deviation (for active ROI): 11.104
Pixel Count: 8463

White SNR: 7.9 (17.9 dB)
White SNR area: 728.7
Appendix C: Sample Report for Filtering Technique Using PhotoES_AM Plugin for ImageJ

Measure 15 gray-scale wedge mean int and var

Mean/Var(1): 130.0/9.58
Mean/Var(2): 130.0/9.58
Mean/Var(3): 130.0/9.58
Mean/Var(4): 130.0/9.58
Mean/Var(5): 130.0/9.58
Mean/Var(6): 130.0/9.58
Mean/Var(7): 130.0/9.58
Mean/Var(8): 130.0/9.58
Mean/Var(9): 42.0/9.48
Mean/Var(10): 42.0/9.48
Mean/Var(11): 42.0/9.48
Mean/Var(12): 42.0/9.48
Mean/Var(13): 42.0/9.48
Mean/Var(14): 42.0/9.48
Mean/Var(15): 42.0/9.48

Filtering method using local statistics and targets from ROI

Measurement No: -2
Width: 418
Height: 411
Node coordinate X: 330
Node coordinate Y: 50

7 x 7 matrix with central pixel [130.0] in (343,273):
Average Intensity/Variance for 7x7 matrix: 111.612/1306.409
*** g_mag(45.3) > ThreshMin(16.0) ***
Subset [12] average/variance: 129.89/6.46
Noise Variance [posit= 8 <-> 9 ]: 9.5
*** sigma_noise > v_var_dir7x7
------------------ end of (343,273) ------------------

7 x 7 matrix with central pixel [130.0] in (541,301):
Average Intensity/Variance for 7x7 matrix: 92.632/1938.320
*** g_mag(87.1) > ThreshMin(16.0) ***
Subset [12] average/variance: 130.25/10.41
Noise Variance [posit= <-- 1 ]: 9.5
Estimated intensity value (Q_ij=0.83/k_ij=0.07): 130.2
------------------ end of (541,301) ------------------

7 x 7 matrix with central pixel [48.0] in (542,301):
Average Intensity/Variance for 7x7 matrix: 79.734/1954.990
*** g_mag(88.3) > ThreshMin(16.0) ***
Subset [0] average/variance: 41.96/17.41
Noise Variance [posit= 15 --> ]: 9.4
Estimated intensity value (Q_ij=7.96/k_ij=0.45): 44.7
------------------ end of (542,301) ------------------
About the Author

Alexander Mraz received a Master’s Degree in Civil Engineering from Slovak University of Technology in 1997 and. In 2001, he entered the Ph.D. program at the University of South Florida.

While in the Ph.D. program at the University of South Florida, Mr. Mraz was very active in research projects with Florida Department of Transportation, which were evaluation the feasibility of imaging vehicle for pavement survey. He has also coauthored two publications and made several paper presentations at meetings of the Transportation Research Board.