Michigan Technological University

# Characterization of Unpaved Road Condition Through the Use of Remote Sensing

## *Deliverable 3-A*: Remote Sensing the Phenomena of Unpaved Road Conditions

Submitted version of:
March 15, 2012

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www.mtri.org/unpaved

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# Acknowledgements

This work is supported by the Commercial Remote Sensing and Spatial Information program of the Research and Innovative Technology Administration (RITA), U.S. Department of Transportation (USDOT), Cooperative Agreement RITARS-11-H-MTU1, with additional support provided by The South East Michigan Council of Governments (SEMCOG), the Michigan Transportation Asset Management Council (TAMC), the Road Commission for Oakland County (RCOC), and the Michigan Tech Transportation Institute. The views, opinions, findings, and conclusions reflected in this paper are the responsibility of the authors only and do not represent the official policy or position of the USDOT, RITA, or any state or other entity. Additional information regarding this project can be found at www.mtri.org/unpaved.


# Purpose of this Document

This document describes the kinds of phenomena, both fundamental (e.g. color) and emergent (e.g. long, linear, patterns due to rutting), which will be important to be able to sense for understanding and evaluating the conditions of unpaved roads. The resulting descriptions of useful phenomena will be used in specifying the sensor(s), as well as in the choice of image processing algorithms. The design of the system is based, first, on the physics of the sensing process.

In addition, this document serves to define precisely the definitions of terms that will be used throughout the rest of this program to describe image characteristics that will serve as discriminants of road distress.

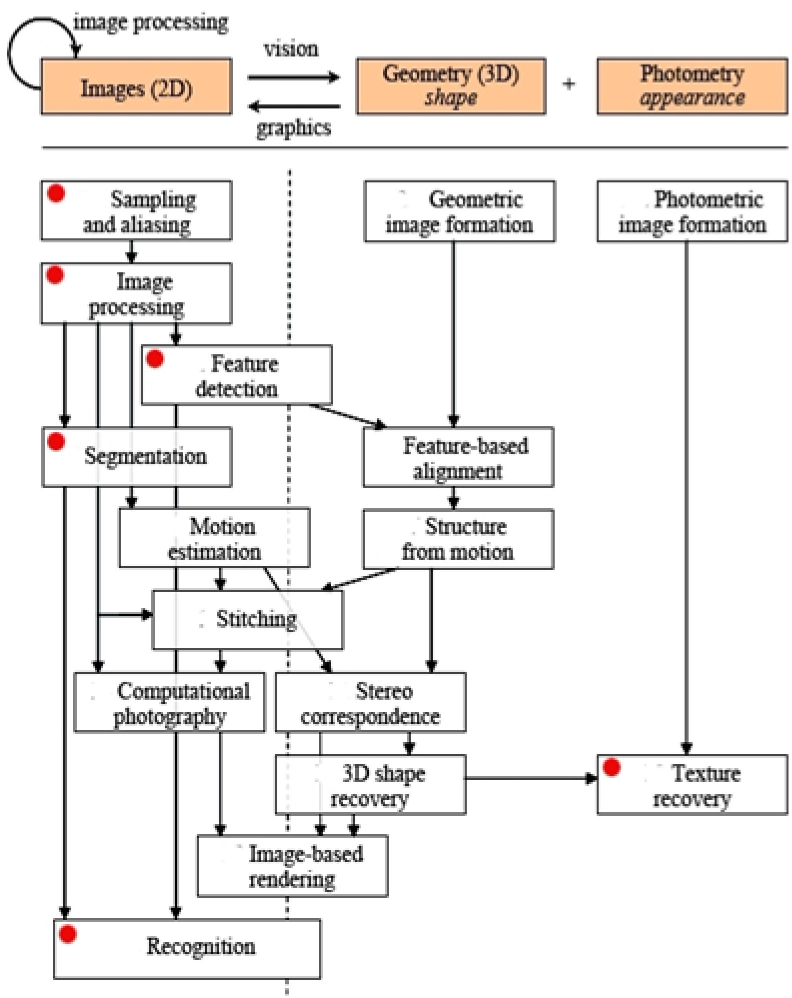
# Motivation

Unpaved road condition can be assessed visually; the texture, color, shapes, surface imperfections, and other characteristics allow us to identify and classify various problems with the road. What can be measured is produced by the interaction of light with the road surface. These are the phenomena that are important. These fundamental phenomena combine to form textures, patterns, and other features that we would recognize as a "distress". In this document, we will be discussing both the fundamaental physics-based phenomena (e.g. spectral reflectance), as well as the emergent features (e.g. texture) that result from variations in those phenomena.

This process of measuring and extracting information from the images needs to be performed automatically. The observable phenomena are the data with which we have to work, and these must be understood in order to choose the best system/algorithm combinations. This process of sensing, and then making sense of the images automatically, is termed "machine vision" [24, pp. 3].

The problem of reconstructing the characteristics of a scene from imperfect and/or incomplete measurements is usually referred to as an "inverse" problem. Machine vision falls into this category. Because there are many possible reconstructions from any set of partial measurements, this is a difficult problem. Although a human 2-year-old can, for example, count all the animals in a picture, this is extremely problematic for a computer. The same is true for unpaved road conditions; while a person can almost instantly recognize and characterize, say, corrugations in a road surface, getting a computer to do this is not a solved problem, and will be imperfect.

Machine vision has been improving gradually; over the last 15 years, we have seen an impressive gain in automatically measuring and understanding images. The figure below[24, pp 20] is an attempt to show how various operations in machine vision are related to our problem of sensing certain physical characteristics of the surface.




The blocks with the red dots indicate those parts of the road-characterization process that are influenced by the combination of phenomena and surface features. In our application, the problem becomes one of determining the important observable features, measuring them, and converting those measurements to information about the road condition. This later process will be considered in a subsequent task, but it is important to keep the goal in mind when considering the types of phenomena that we can sense, and the types that we want to sense to be able to solve the problem.

The process begins with the (much easier) forward model, by understanding how the incident (sun)light interacts with the surface, then enters the optics, where it is altered, and finally strikes the sensor, where some part of it is measured. The resulting images will have characteristics unique to the types of distresses we want to measure; color, texture, contrast, long-range patterns, etc.

The remainder of this document will detail the kinds of image characteristics (both fundamental and emergent) which are important to sense, to be able to identify distresses.

# The Surface Characteristics

The road surface is all that we can measure in the optical spectrum; the subsurface structure may affect the surface, but we cannot sense it directly. There are a variety of observable characteristics which can be used to extract distresses from optical images.

## Color

While roads themselves may be many colors, depending on the material content and the conditions, the spectral characteristics of the surface may change when a distress is present. Before we consider the particular spectral changes of interest, some background on color content is introduced.

### Background

Human color perception is based on the incidence of visible light (with wavelengths in the 400 to 700 nm range) upon the retina. Since there are three types of color photoreceptors in the retina, each with a different spectral response curve, all colors can be completely described by three numbers. In 1931, the Commission Internationale de l'Eclairage (CIE) adopted standard curves for the color photo-receptor cone cells of a hypothetical standard observer, and defined the CIE XYZ tristimulus values, where all visible colors can be represented using only positive values of X, Y and Z. Since the creation of the CIE XYZ, other color spaces have been established to specify, create and visualize color information. The RGB (red-green-blue) color space, as used by graphic displays, can be visualized as a cube with red, green and blue axes. Different applications (e.g. printing) have different needs which can be handled better using different color spaces (in the case of printing, the CYMK). We will be considering only RGB in this discussion, since this is the most common one for camera images.

### Road Surface Color

Road surfaces come in many colors, and it is unlikely that absolute color will be a strong characteristic of any particular distress. However, color contrast changes can be characteristic of surface changes. These changes from one area to another may be normal, or may result from distresses. In either case, we need to be able to characterize the color changes in a consistent way. Later, we will decide whether particular changes are associated with particular distresses.

We have collected sample images of various road surfaces. To be able to compare colors quantitatively, we placed a gray-card (of known color content) in the scene; the images, regardless of the lighting, can then be corrected to compare colors, as needed. The images below show how lighting and camera effects can change the measured color in a scene (see Figures 1 and 2).


**Figure 1: Example of how lighting and camera effects can change the measured color of a scene.**

Note that the identical gray-cards in the scenes above in Figure 1 appear to be different colors. This is probably due to camera white-balance errors due to lighting differences. If we were using uncorrected (absolute) color as a metric, we might be led to believe the scene on the left had a “bluer” surface than it actually does; some color correction would be needed to compare the spectra of these two images. A corrected version is shown below in Figure 2, in which the grays are equalized. It can be seen that the surface is much more yellow than blue, once corrected.


**Figure 2: Example images with the grays equalized; this reveals that the surface on the left is much more yellow than it originally appeared in the digital image.**

This correction is needed during evaluation, to determine how much lighting affects color changes (e.g., if a cloud obscures the sun during a measurement, what is that effect, versus a “real” surface color change). If lighting/color effects are important in determining certain distresses, then the design of the sensor system must include a way of characterizing the lighting, as well imaging the surface.

## Texture

While color is a purely single-pixel property of images, texture involves a spatial extent; a single pixel has no texture. If texture is defined in the frequency domain, the texture of some particular location in the image is characterized by the frequency content in a neighborhood.

The texture is itself produced by some spatial change in color or contrast that has a characteristic spatial extent. It is important that we be able to sense all textures of interest (which comes down to a spatial resolution requirement). In our case, the road surface will have a number of textures, some of which will be characteristic of roads in good condition, and some of which will be characteristic of a damaged surface. The key here is in being able to measure, abstract, and associate various textures with various road states.

Numerous approaches for the representation of textured images have been proposed, ranging from the means and variances of a filter bank output [7, 13], wavelet coefficients [20], wave-packets [14], fractal dimension [2], or parameters of an explicit Markov random field model [3, 18]. Comparative studies on this subject can be found in [6,19,20]. Gabor filters are often used for texture analysis and have been shown to exhibit excellent discrimination properties over a broad range of textures [12, 13, 25]. These will be evaluated in a later task, but an example of segmentation using a Gabor filter is shown below in Figure 3.

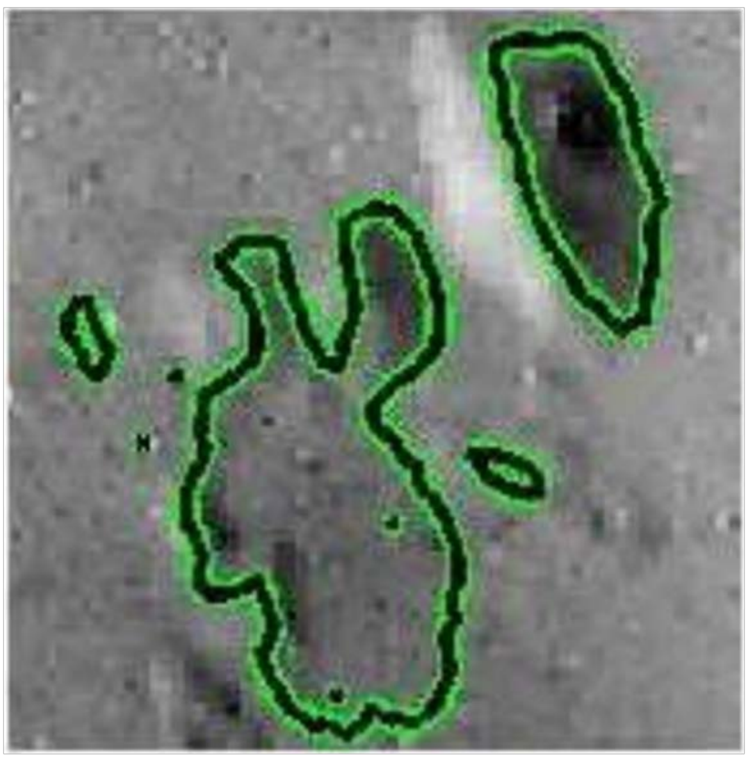


**Figure 3: An example of segmentation using a Gabor filter.**

As with many filtering operations, the filter bank used must be tuned to the texture being extracted. The local (small area) surface texture may change when a distress is present. That is, the texture of a surface which is losing (or has lost), for example, its coarse material will indicate damage, and filters would be designed for this.

### Textures of Interest

The presence of aggregate as part of the road surface will produce a characteristic texture. This texture will change based on the size of the aggregate and its composition. Loose aggregate is expected to contain much coarser material, and thus have a different characteristic texture than a packed surface.

As road surfaces lose material, it is expected that the texture will change; the differential textures from one section of road to another can be used to differentiate the surface condition. Whether these changes reflect damage, or impending damage, will be determined once measurements commence.

Since the current requirements on surface features specify that certain distresses need to be measured to an accuracy of 1-2 inches (see the requirements definition report at [http://geodjango.mtri.org/unpaved/media/doc/deliverable_Del1-A_RequirementsDocument_MichiganTechUnpavedRoadsr1.pdf](http://geodjango.mtri.org/unpaved/media/doc/deliverable_Del1-A_RequirementsDocument_MichiganTechUnpavedRoadsr1.pdf)), the sensor itself must be capable of sensing at least half that spatial resolution; this is the Nyquist-Shannon sampling criterion[23]. This sampling should include texture.

## Patterns

Related to textures are what we will term “patterns”. These tend to be repetitive combinations of textures that can be either long-range, or local, and are characteristic of road surface features.

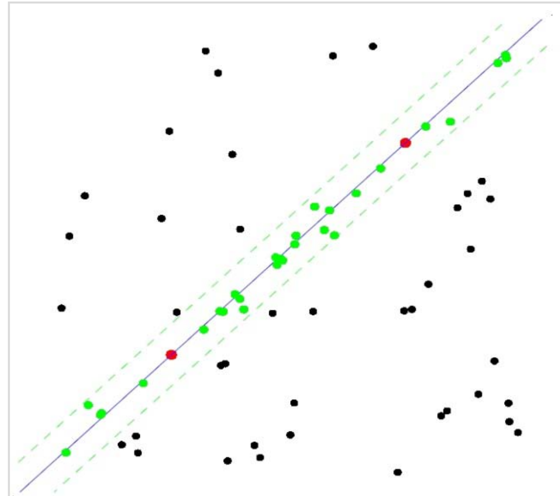
Long-range spatial patterns may characterize certain distresses. For example, corrugations are characterized by repetitive contrast changes across the road surface, while rutting is characterized by longitudinal (along the direction of travel) edges in the image. Both, however, are linear features that emerge from contrast changes due to material variations . Other such patterns include ovals (characteristic of potholes).

There are several important properties of the patterns that, while not physical phenomena, are key to differentiating the damages. These are:

1. The location of the patterns on the road: lines in the traveled lane will tend to be rutting, while lines outside that lane are likely to be berms of displaced material.
2. The orientation: ruts only form in the direction of travel, while washboarding only forms across the direction of travel.
3. The scale: ruts tend to be on the order of a tire-width, while washboarding tends to be much wider. These types of scale-dependent characteristics have been widely used in multiresolution techniques such as wavelet analysis [14, 20].

There are several common ways of detecting patterns, including successive approximation (where curves are recursively divided into smaller lines), Hough Transforms (in which edges “vote” for plausible curve fits), and Random Sample Consensus (RANSAC) (in which randomly selected edgles are tested against shape hypotheses) [24, pp 224]. An example of detecting a line using RANSAC is shown below in Figure 4.

**Samples of some 2-D measurements**



**Best line after pair-wise testing of all possible lines**

**Figure 4: An example of detecting a line using Random Sample Consensus (RANSAC) .**

In the data above, left, the human eye can discern a linear feature, but computer algorithms to isolate that feature will have various trade-offs between performance and execution time. RANSAC, for example, is more efficient of memory, but can take much longer to run. The choice is problem-dependent, and must be determined once data have been gathered.

## Profile

The profile of the road surface is a 3-dimensional characteristic. That is, it can be described by the position on the road surface (both in the travel direction, and side-to-side), and the height at each position. This 3-D information is useful in determining not only long-range details, such as loss of crown, but also local patterns that may develop. The mean profile depth may be used in local regions as one metric of surface condition. The change of this from the center to the edge of the road can be used to determine crown.

The problem is one of determining, inexpensively but accurately, this mean profile depth from a series of 2-D images. This has been an active area of machine vision research for decades[24]. Since our sensor will be moving rapidly, and we have no plans to loft a stereoscopic sensor, we will be using a method call “structure from motion” [4], which recovers both the scene and the camera motions from a series of static images without assuming anything about the cameras, scene content, or correspondence between images.

One possible method of doing this is to use a set of scale-invariant image features [17], and obtain the optimal motion and structure by minimizing the reprojection errors between the observed and predicted image points using Levenberg-Marquadt optimization[16]. This method will be evaluated to determine the requirements on the sensor to be able to achieve the sampling needed to meet the texture and profile requirements. An example of such a reconstruction is shown below in Figure 5.

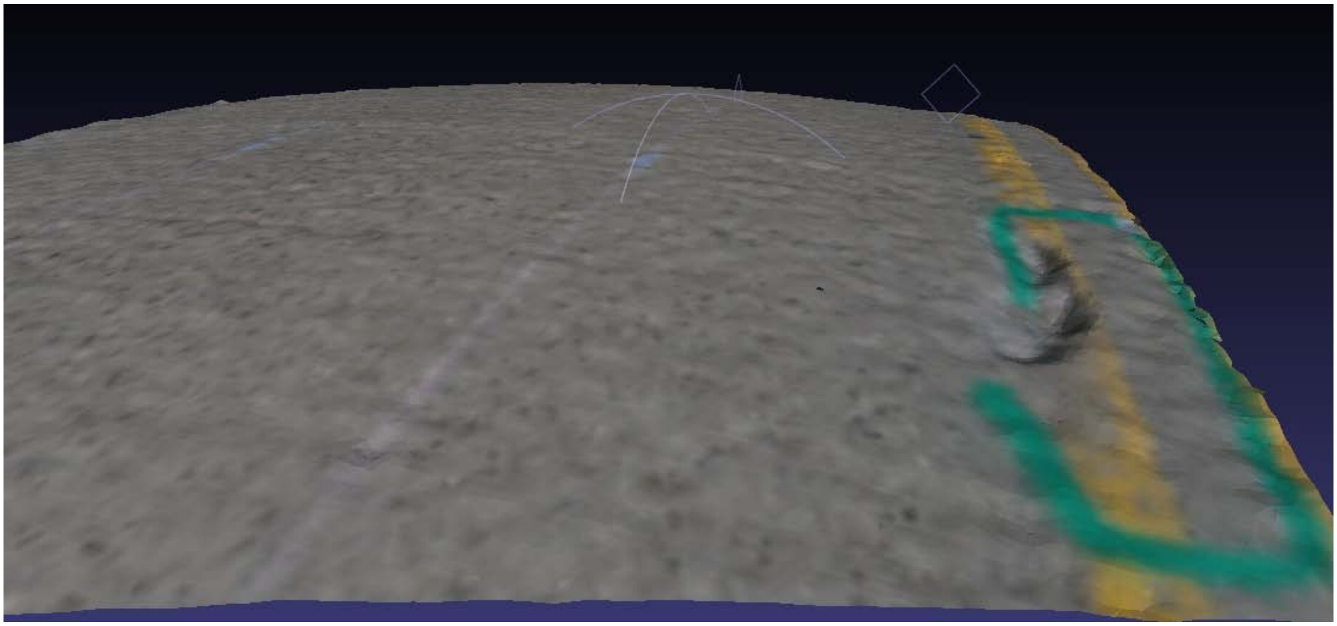


**Figure 5: An example of a 3-D reconstruction for a road surface using structure from motion methods.**

This is a view of a 3-D reconstruction of a section of the Freer Road bridge, showing both texture, and a large pothole (center right). It is difficult to illustrate in a 2-D format, but detailed depth information can be extracted from this reconstruction. Both road crown and local characteristics can be extracted from these types of 3-D features.

## Polarimetric backscatter

It has been shown that road surface defects have characteristic radar polarizations[15], as well as polarimetric signatures in the infrared[9]. It is possible that optical polarization, while weak, may serve as a way to detect loss of surface material. This effect is being investigated in the laboratory at this time; weather conditions so far have prevented field measurements from being made. Preliminary indications are promising. The picture below shows the laboratory equipment which will be used to collect the polarization data.

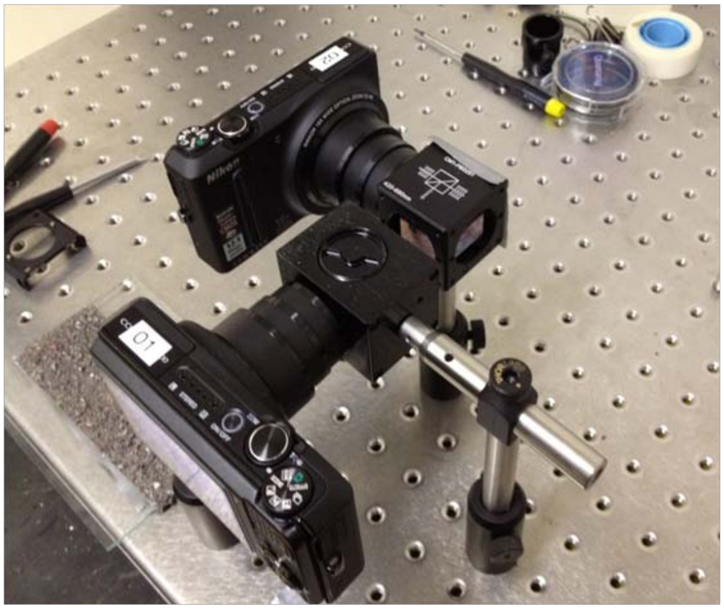



**Figure 6: Example of the camera setup being used in the laboratory to investigate the potential of optical polarization in helping to detect loss of surface material.**

The system consists of two cameras observing the same field-of-view through a polarizing beamsplitter. Once properly aligned, the two images can be compared on a pixel-by-pixel basis for difference in polarization.

## Summary

The only characteristics that can be sensed optically are surface phenomena. These include color, texture, patterns, profile (i.e. 3-D structure), and polarization. The requirements on distress measurements have been detailed previously; the phenomena associated with these distresses will need to be determined once data become available. This document has described explicitly those phenomena for which we will be testing once the sensor is designed and built. This will inform the sensor selection, which is the focus of the next report, Deliverable 4-A, "Candidate and Recommended Remote Sensing Platforms for Unpaved Road Condition Assessment."

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