Visual Appearance of Surface Distress in PCC Pavements: I. Crack Luminance

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Visual examination is widely used for evaluating the extent and severity of pavement distress. The visually assessed pavement surface condition is combined with structural information to rate the pavement on the basis of scoring systems that have been developed by the state transportation agencies to evaluate which pavement sections require regular maintenance, overlay, or complete reconstruction. Although scoring is often computerized, the raw data are usually collected by slow, laborious manual and visual methods during site inspections by trained field personnel and they are input into the computer manually. These methods are expensive and prone to subjectivity, error, and nonrepeatability. Automated surface distress evaluation has not developed rapidly because the accuracy of automated systems has not been sufficient to inspire confidence among the pavement engineers who have to rely on the evaluation results. System accuracy can be enhanced by using better engineering methods and data in designing the image acquisition and image processing portions of automated inspection systems. The visual signal—the apparent luminance of cracks in portland cement concrete (PCC) pavements and the contrast that they exhibit compared to surrounding pavement surfaces—is the input to the automated inspection system. The luminance depends on the reflectivities of the paving materials. Reflectivity measurement methods are specified and data are tabulated. In a companion paper in this Record computer modeling methods for determining and analyzing crack luminance are reported. The methods and data presented in these papers are useful for designing automated pavement inspection systems.

The deterioration of transportation systems in the United States is a problem of major concern to local, state, and federal agencies and to the public. Highways in the United States are deteriorating at an alarming rate due to normal aging processes and to traffic loads that exceed design limits. The nation's economic growth is critically dependent on a sound highway pavement system. The projected cost for maintenance through the year 2000 is estimated to be hundreds of billions of dollars, a problem compounded by decreases in available funding for restoration of this vital element of the infrastructure. Financial improvements are not expected, as maintenance and construction costs increase due to inflation in material and labor costs and as revenues decline.

This discouraging picture has prompted development and utilization of more efficient and systematic procedures to assist transportation agencies with their pavement management systems (PMSs) (*1*). An increasing number of state transportation agencies are utilizing PMSs to provide current and accurate assessment of the condition of highway pavements and to allocate available funds efficiently for pavement restoration (*2–6*). A PMS is generally used for evaluation of statewide pavement surface condition, analysis and evaluation of structural adequacy, development of alternative maintenance and construction strategies, and selection of an optimal pavement management strategy. Surface evaluation provides the data necessary to judge the service adequacy of existing pavement, to determine if structural evaluation is necessary, to determine the probable causes of surface distress, and to estimate needs and priorities for preventative and corrective maintenance (*3*).

Evaluating the extent and severity of surface distress requires the acquisition of large amounts of visual data, typically obtained by on-site inspection. The pavement surface condition is rated using a pavement distress index based on scoring systems that have been developed by the state transportation agencies to determine if a pavement section requires maintenance, overlay, or reconstruction. The scoring systems are customized for the different pavement construction and maintenance practices used by the respective agencies. Although the computation process is usually computerized, the raw data are still input manually, a laborious and expensive task, in addition to the slow and laborious manual and visual data collection during site inspections by trained field personnel. These methods are inefficient and can lead to a high degree of subjectivity, error, and nonrepeatability in the measurements.

Thus, the need for an automated visual pavement surface distress system is increasingly evident. A number of research and development projects have been carried out by national and state transportation agencies and private companies; to date, these projects have displayed only limited success. However, the effort to understand the nature of the problems and to develop pertinent research and engineering methods and data will make future attempts more successful.

BACKGROUND

There are two major steps in automated pavement inspection—an image acquisition system obtains images of pavements, and an image processing system evaluates those images to assess the severity and extent of surface distress. In this section, the approaches that have been attempted, the difficulties encountered, and the engineering methods and data that can facilitate further automated inspection efforts are discussed.

Image Acquisition

The image acquisition system that looks at the pavement comprises the camera, the lens, and the computer hardware. Distinguishing between distressed and sound pavement surfaces

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is easy for a human but difficult for a machine vision system. Whereas the human retina contains nerve tissue specifically dedicated to the task of detecting thin, discontinuous features such as cracks in images, a machine vision camera contains no such specialized receptors. Its output, a voltage proportional to the amount of light falling on the sensor, is sampled by a frame grabber to produce a digital image made of picture elements (pixels) that are laid out in a grid-like pattern across the image of the pavement. The digital image is just a matrix of numbers, each of which represents the amount of light from a discrete area on the pavement surface that is imaged into the corresponding pixel. These numbers are called "gray levels"; the higher a number, the lighter the corresponding shade of gray in a pixel. The goal of the image processing system is to identify various types of surface distress from the matrices of gray level numbers that represent images of pavement surfaces. Finding cracks in digital images happens during the image processing step.

The image acquisition system must acquire information that is adequate to meet highway maintenance needs. A reasonable acquisition specification is that the system observe 100 percent of the road surface and that it be able to detect cracks 1/16 in. (1.5 mm) wide within a 12-ft (3.7-m) lane from a vehicle traveling at 55 mph (90 km/h). Successful detection means that the probability that crack gray levels are distinguishable from surface gray levels is acceptably high—an acceptable percentage of false positives, apparent cracks that are only artifacts of the image acquisition system, and false negatives, cracks that escape detection, are usually included in the acquisition specification. There are two problems with designing an acquisition system capable of meeting such a specification—resolution and data bandwidth.

The specification implies the ability to resolve cracks only 1/2,400 of the lane width. Although such resolution is comparable to the capabilities of the human eye (*7*), it greatly exceeds the resolution of commercially available television cameras, which typically have only about 500 pixels per line. Even that number is an overestimate of the camera's resolution. When the image of a crack is less than two pixels in width, the image contrast (the relative difference in the video signal between the light and dark image areas) is greatly reduced. The only way to ensure that small cracks do not escape detection is to ensure that the image acquisition system has an equivalent pixel count of at least 4,800 in the direction transverse to the lane. The actual pixel count may have to be higher because the apparent crack width can be foreshortened by perspective projection through the camera lens and a crack can appear as much as 30 percent narrower than it actually is, depending on how close it lies to the edges of the lane and the camera's height above the pavement surface.

The bandwidth problem concerns the rate at which image data are generated. The acquisition specification under discussion requires a video bandwidth of greater than 30 MHz. If video signals are stored digitally, this rate corresponds to greater than 240 Mbaud, assuming 8-bit gray levels. Commercial video cameras and recorders typically have bandwidths in the 4- to 6-MHz range, a factor by at least five too low. Thus, image acquisition systems based on the RS–170 (*8*) commercial video standard generally have insufficient signal bandwidth for pavement inspection, unless multiple cameras are used or unless one or more of the constraints on speed, coverage, or minimum crack size are reduced.

Several approaches have been used in the past to acquire video images for automated pavement inspection. The system developed at the University of Waterloo (*9*) uses an RS–170 camera and has a resolution of only about ¼ in. (6.5 mm). Even systems with multiple cameras have not yet achieved sufficient resolution and coverage (*10*). Nonstandard systems with line-scanning arrays (*11–13*) can solve the resolution problem, but still require the processing of enormous amounts of data, also true for pavement inspection systems that analyze films exposed to photologging equipment. One technique for solving the data rate problem is real-time data analysis: only summaries of the data are retained. The system built by Ektron for FHWA uses analog signal processing to identify pavement distress signatures in signals obtained with custom cameras. That system has reduced data rates but it may not be sufficiently reliable for general pavement evaluation use. Another disadvantage is that it destroys the raw video data, which can be important to a pavement engineer assessing the nature of the distress in making maintenance decisions. Finally, image compression is a useful technique for greatly reducing the amount of visual data that must be processed or stored (*14,15*); however, developing compression algorithms suitable for pavement images would require a better understanding of the nature of the visual information than is now available. No digital image acquisition system that is capable of meeting the acquisition specification under discussion is presently known.

What information would allow the designer of image acquisition systems to meet the specification? Cracks are visible because they are darker or lighter than the surrounding pavement surface. The image contrast depends on the depth and width of the crack, the reflectivity of the paving materials, the alignment of the crack with the light source, and the viewing direction. Carefully matching the image contrast, camera optics, and the camera sensor characteristics can ensure that there is sufficient image contrast for the image processing system to meet its specification reliably (*16,17*). Therefore, understanding and characterizing the inherent crack contrast in pavement images is a first engineering step in designing an image acquisition system. That understanding, which is also necessary to the design of image analysis and compression algorithms, is universally applicable to the design and analysis of all automated pavement inspection systems.

Image Processing

Once supplied with images of sufficient contrast to assure that cracks are detectable, the next step is to use image processing, a sequence of mathematical operations or algorithms performed on a digital image, to detect those cracks. There are hundreds of image processing algorithms available to the vision system engineer (*18–27*). Traditionally, image processing algorithm selection has been a heuristic process with few numerical measures of success; algorithm effectiveness is often demonstrated by before and after images. Successful pavement surface distress detection requires selecting a sequence of algorithms that reliably locates pavement distress and that fits within the available computing assets. (Some algorithms take considerably more computing power than others.) The methods and data presented in this paper can provide a basis for evaluating the algorithms objectively on the basis of the probability of detection.

The rows and columns of the digital image are typically aligned with the transverse and longitudinal directions of the lane; the initial image processing algorithms are intended to determine which row and column intersections contain gray levels that indicate cracks or patch edges at the corresponding points on the pavement. These algorithms are local operators because they operate locally to determine whether or not each pixel is part of a crack. A second class of algorithms, global operators, string together adjacent pixels of the same type to determine the size and orientation of each crack or patch. These are the algorithms that classify and measure pavement surface distress from the locations of crack and patch edge pixels. Global algorithms fail if the local algorithms do not provide the correct information. Hence, in this paper the nature of the data that the local algorithms analyze is emphasized.

Many factors contribute in making the data difficult for local algorithms to interpret correctly. Lighting on the pavement changes with the time of day, amount of cloud cover, and presence of shadows of fixed and moving objects on or near the road. Aggregate in the paving material makes up a much larger portion of the information in a pavement image than does surface distress. (The characterization of aggregate appearance on the pavement surface is beyond the scope of this paper, but it is required for a complete understanding of the visual appearance of distressed pavement.) The reflectivity characteristics of the pavement surface change with wear and with weather conditions. Other markings or objects on the road, such as oil stains, skid marks, lane markings, dirt, and debris can confuse the distress detection and classification process. Understanding and characterizing of all of these effects is a necessary prelude to algorithm selection.

A class of local algorithms that is very useful for detecting surface distress is the edge finder. These algorithms locate edge pixels by searching for distinguishing characteristics in the digital image. One typical algorithm, the thresholding algorithm, labels any pixel darker than some preset value or that has a gradient higher than some preset value as belonging to a crack. Because they are fast and easy to implement, thresholding algorithms are frequently used for locating pavement cracks (*9–12,28,29*).

Unfortunately, thresholding algorithms are not particularly reliable edge finders. Figure 1 shows a photograph taken in direct sunlight of alligator cracking in an asphaltic concrete pavement. The resolution of the 35-mm film used to produce this photograph exceeds that of any commercially available machine vision camera and the film's usable contrast range is greater than that of a camera's sensor. In a digital image of distress acquired on a sunny day with a commercial, solid state, RS–170 video camera (Figure 2), camera limitations reduce crack sharpness and contrast. The top half of the figure shows a photograph of the digital image. The white horizontal line denotes a typical pixel row in the image. In the bottom half of the figure, a graph of the gray levels in a typical matrix row indicates the difficulty in designing an edge finder suitable for detecting pavement distress. (High values in the graph correspond to light pixels; low values are dark.) Extrema in both the gray-level signal and in its derivative can be found at the edges of both cracks and aggregate, making it difficult to distinguish between them. In other words, some pieces of aggregate are as dark as the cracks, and some aggregate edges are as sharp as the edges of cracks.

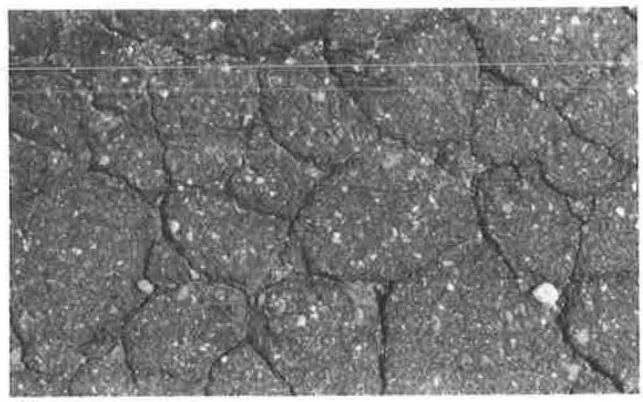

FIGURE 1 Photograph of alligator cracking in an asphaltic concrete taken with a 35-mm camera.

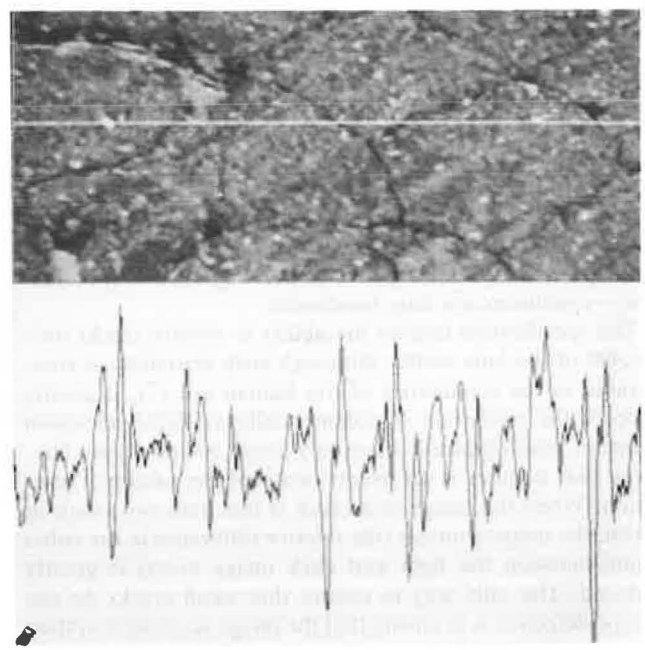

FIGURE 2 Digital image of alligator cracking.

Other edge finding algorithms also have difficulty with pavement images (*10*). No edge finding algorithms are known that can reliably detect cracks in images of this quality nor is any way known to design acquisition systems in whose digital images cracks can always be distinguished from aggregate by simple edge finders.

These figures also show the differences in the way cracks appear to humans and to machine vision cameras. In the photograph (Figure 1), narrow cracks are as dark as wide cracks. In the digital image (Figure 2), the narrow cracks have significantly reduced contrast and can even disappear completely. The fact that a crack is readily apparent to the eye is no guarantee that a camera can see it; the human eye is a poor substitute for objective measurement in evaluating image processing algorithms.

Probability of Detection

What are objective measures for evaluating image acquisition systems and image processing algorithms? How are crack luminances used in these evaluations? One criterion is crack detection probability. To meet a minimum crack detectability contrast specification, the gray level of a crack pixel, in combination with the gray levels of surrounding pixels, must be different enough from the gray levels of sound pavement pixels for the crack to be detected. Although the methods for calculating this minimum gray level difference for any specific machine vision system are beyond the scope of this paper, such a value exists and forms the upper bound to actual system performance; any real edge finder will degrade this value and hence produce more errors than the theoretically calculated error rate.

In judging whether a machine vision system, in principle, can reliably detect cracks, the machine vision system design engineer calculates the minimum acceptable image crack contrast using crack luminance values, camera models, and other system design parameters. This parameter must exceed the minimum crack detectability contrast, which is calculated from minimum crack size and detectability values in the image acquisition specification. In testing algorithms, digital images can be altered to replace crack pixel gray levels by the minimum detectability values to create worst case images. These images can be used to ensure that the algorithms operate effectively. Crack luminance values are useful because they characterize pavement images during both design and testing of both parts of the image acquisition system. In the next section, why cracks appear to have the luminances they do is explained.

CRACK LUMINANCE

In the last section, it was established that the crack luminance (the fraction of light reflected into the camera from each portion along the bottom and side walls of a crack) determines the apparent crack contrast, which is used in the design of image acquisition and image processing systems. In this section, the factors that determine crack luminance are discussed.

Reflectivities of Paving Materials

Pavements are visible because they reflect light. The luminance of each visible surface, including crack sidewalls and bottom, is proportional to the total amount of illuminance they receive and their reflectivities. In this section, the results of reflectivity measurements made on paving materials and the conclusions that can be drawn for crack detection are discussed. In a later section on reflectivity measurements, details of light reflection from paving materials are described and the equipment and techniques used to make measurements of the reflectivity are outlined. It is this reflectivity value that is used to characterize a surface.

The reflectivities of mortar, isolated aggregates, and portland cement concretes are measured using the equipment and methods described in a later section. Mortar has a reflectivity of 0.30 to 0.35 for both freshly prepared surfaces and for cut or fractured surfaces; that means between 30 and 35 percent of all of the incident light is reflected back from its surface. Although the aggregate materials measured were chosen with mindful regard that their availability, price, and structural properties be compatible with their use in PCC pavements, a primary selection criterion was that materials were wanted with as wide a range of reflectivities as possible. Figure 3 shows a photograph of some of the aggregate samples measured. The materials, clockwise from top left, are schist, feldspar, chert, marble, basalt diabase, basalt, and organic shale. As shown in Figure 4, the least reflective materials (organic shales and magnetites) have reflectivities as low as 0.05, and the most reflective material (marble) has reflectivity above 0.65 and as high as 0.90. These values are only representative; measurements should be made on the specific aggregates used in any pavement being analyzed. The reflectivity range shown in Figure 4 is enormous—it is comparable to the range spanned

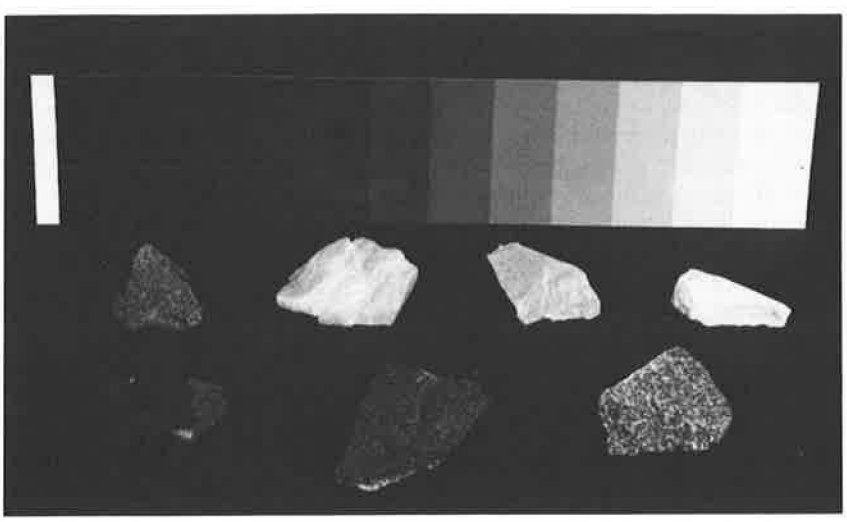

FIGURE 3 Photograph of typical aggregate samples used in the reflectivity measurements and a step wedge reflectance standard (with reflectivity ratio between adjacent steps of $\sqrt{2}$ = 1.414).

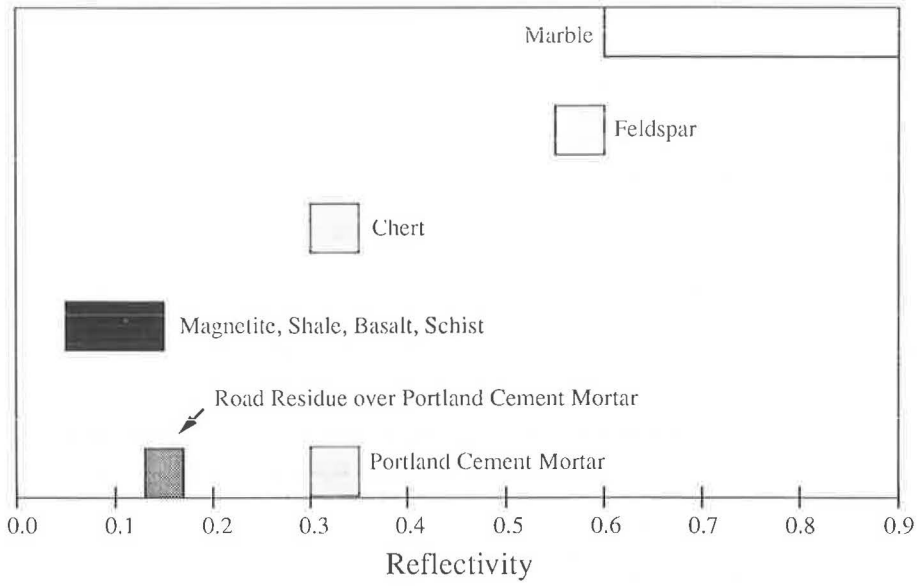

FIGURE 4 Reflectivities of some aggregate materials chosen for the maximum reflectivity range.

by the least and most highly reflective household materials, black velvet and white paper, and it exceeds the contrast ranges of almost all commercially available cameras.

It was also of concern that weathered and worn PCC pavements might differ in appearance from the freshly prepared pavement samples measured. On material removed from old PCC pavements, the reflectivity of the road surfaces and of both cracked and cut cross sections was measured. The cut and cracked surfaces have reflectivities almost identical to those of freshly prepared portland cement mortar. In general, the worn pavement surface is visually similar to freshly prepared pavement except that the reflectivities of all materials, mortar and aggregate alike, are reduced by a factor of about two (see Figure 4). The most significant difference is that worn pavements exhibit more specular reflection than freshly prepared pavements at glancing angles of illumination and observation, conditions that are unattractive for automated inspection purposes. Thus, the effects of wear and residue can be simulated by viewing a freshly prepared pavement sample through a neutral-density filter or by applying a low-gloss varnish of the appropriate darkness to the sample surface; both methods have been used with success, although the results obtained with varnishes have been less consistent. The ability to simulate the visual effects of wear and aging on pavements is important if the results of laboratory measurements on new samples are to be applicable to analyzing images obtained from old highway pavements.

Luminance Measurements

Luminance of reflecting objects is usually measured by means of a spot photometer, a type of imaging light meter with better spatial resolution and light measurement accuracy than the vision system camera. In measuring the luminance of pavement surfaces, two questions were addressed. First, were the reflectivities measured on laboratory samples of mortar and aggregates adequate to explain the luminance of those materials in PCC pavements? Second, can luminance values that are calculated from material reflectivities adequately explain and predict the luminance of both sound and distressed pavements under all conditions of lighting?

To answer the first question, PCC samples were prepared using a 3:1 weight ratio of uniform quartz sand and portland cement with a water-cement ratio of 0.3. Course aggregate was hand-selected from batches of material whose reflectivities had been characterized. Using simulated sunlight, the luminance was measured on mortar and aggregate on both the prepared pavement surface and on cut and cracked cross sections through the samples. In summary, the luminance values of the mortar and the aggregates in concrete are identical to the values predicted from reflectivity measurements on the parent materials, within the measurement errors of about ±5 percent. In other words, reflectivity measurements on the components of a pavement can be used to predict the appearance of the pavement surface. The reflectivities of other materials found on pavement surfaces—paint, lane markers, patch materials, joint fillers, debris, etc.—have not been measured, but including them in calculations of the luminance of pavement surfaces should be straightforward.

Unfortunately, it is not so easy to predict or explain the luminance of internal crack surfaces, for four reasons. First, the crack bottom and sides can be made of mortar or aggregate, which often have different reflectivities. Cracks usually propagate through the mortar or along the interface between mortar and aggregate (*30*). Therefore, as shown in Figure 5, aggregate can form at most one sidewall or the crack bottom, so the effective reflectivity, and hence the apparent luminance, of the crack will depend on the observation direction. When the crack involves only mortar, the surfaces are homogeneous. In cracks that propagate along the surface of aggregate, one sidewall or the crack bottom can have reflectivity different from the rest of the crack surface. Cracks with aggregate along two sidewalls are unlikely because they would have

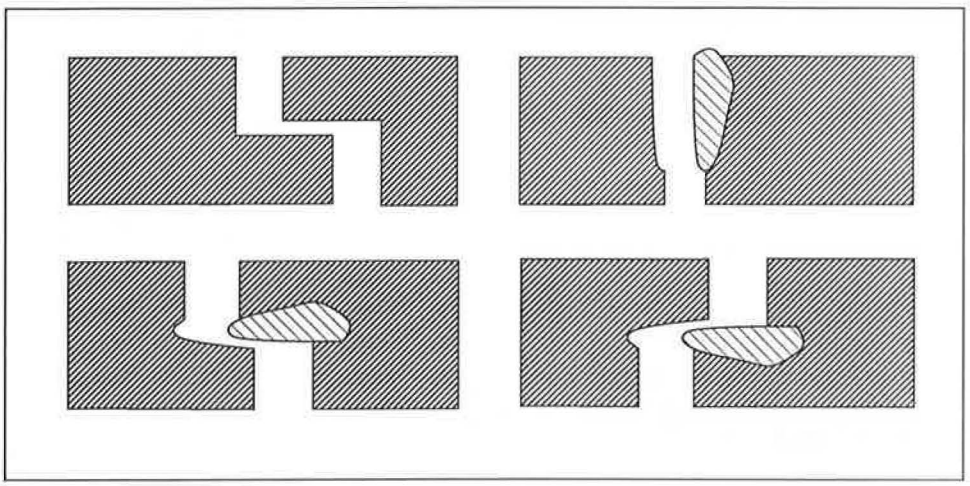

FIGURE 5 Schematic diagrams of cracks in PCC pavements.

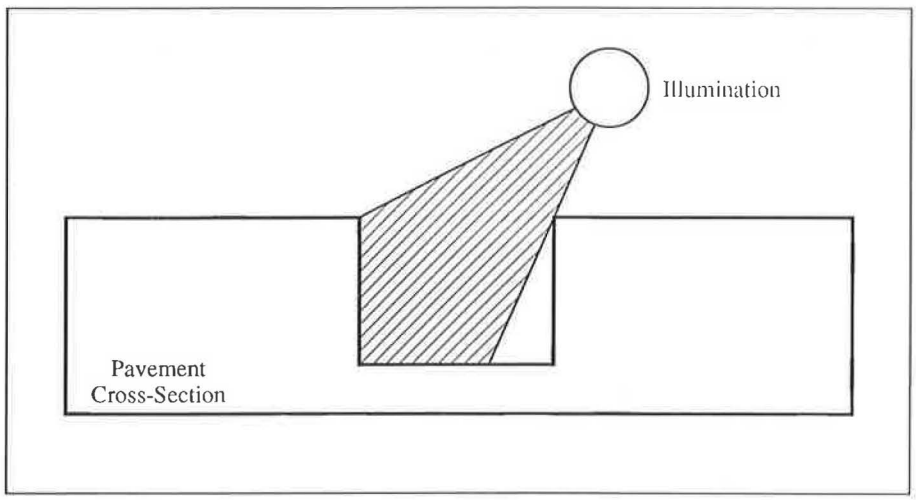

FIGURE 6 Cross-sectional view of an idealized pavement crack.

to result from directly touching aggregate pieces that had not been wet by the paste or from cracks that propagated through aggregate; in properly prepared concrete neither case should obtain. The second problem has to do with the direction of incidence. When the light comes from a small source such as the sun or a lamp, one sidewall, at least part of the bottom, and possibly part of the second wall will be shadowed so they will appear to be less luminous. A detailed description of the lighting is necessary to calculate the effects of this shadowing. This shadowing is shown in Figure 6, which also shows the third problem—different angles of light incidence on the crack bottom and sides. The effective illumination from a small source varies as the cosine of the angle of incidence. The crack sidewalls are roughly perpendicular to the surface and bottom so they may receive the illumination at different angles of incidence. Therefore, unshadowed crack surfaces with the same reflectance as the surface may have different apparent luminances. The fourth problem is also shown in Figure 6. The unshadowed portion of the crack bottom is illuminated not only by direct illumination from the source, but also from indirect illumination received from light reflected off other nearby crack surfaces. In the example illustrated, the crack bottom luminance should be greater than the surface luminance because of this interreflected light.

Examples of these four difficulties are also shown in Figures 7 and 8. A sample of PCC made with selected granite aggregates was cracked and placed on a mechanical slide to allow varying the crack width [set to 3 mm (0.12 in.) in this case]. Figure 7 shows a side view of the sample; the lighting has been adjusted so that the granite aggregate can be seen clearly on the cut side surface. Figure 8a shows a digital image of the top surface of the sample with crack width set to 1.5 mm (0.06 in.). The sample is illuminated crosswise to the crack by simulated bright sunlight at 60 degrees above the horizon. The crack is clearly darker than the surface, because of shadowing. Figure 8b shows the same crack illuminated from the same elevation but along the crack direction, which eliminates shadowing on most of the bottom surface. Interreflection has now caused portions of the crack bottom to be more luminous than the pavement surface. (The brightest pixels in the image are

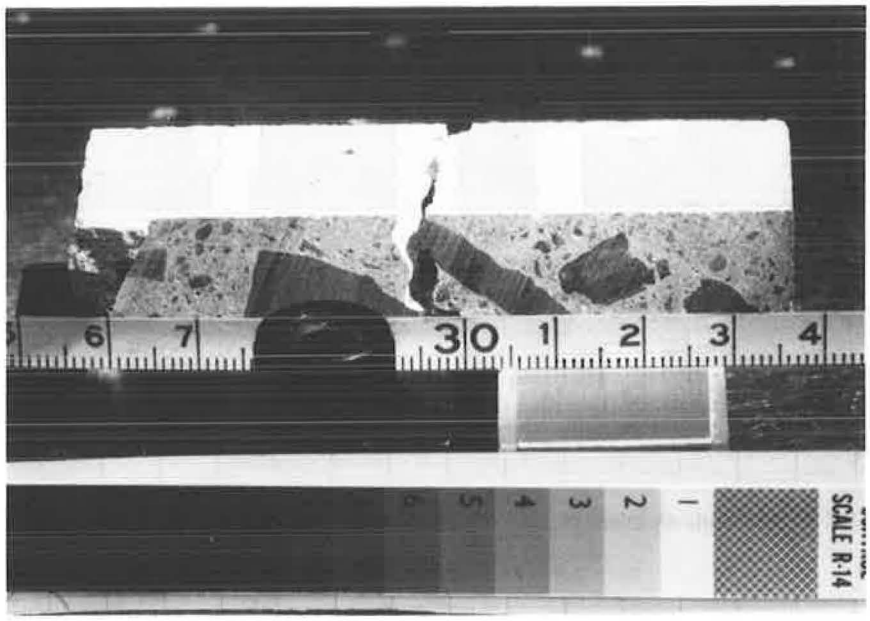

FIGURE 7 Photograph of a cracked PCC sample made with granite aggregate.

inside the crack in the center of the figure.) Where the crack bottom is formed by aggregate, which is less reflective than the mortar, the crack bottom is less luminous than the surface, despite interreflection. The digital images of Figure 8 were used for luminance measurements so the resolution is much better than an automated pavement inspection system would display. In that case, the crack in Figure 8a would be easily detectable but the crack in Figure 8b would appear as discontinuous pixels, some with gray levels higher than the surrounding pavement and some with lower values. Designing an image processing algorithm that can reliably detect the crack in Figure 8b is most challenging.

Figures 8a and 8b show the same physical crack, only the lighting has changed. Because cracks come in all orientations, the same crack can have different detectability at different times of the day; or, some lighting conditions emphasize transverse over longitudinal cracks.

In summary, the surface luminance of pavements is easy to understand and to predict but the crack luminance is a complicated function of many parameters—the reflectivities of all of the paving materials, illumination direction and intensity, and crack size and orientation.

DISCUSSION

In the last section, the factors that affect apparent pavement luminance, material reflectivities, illumination conditions, and crack geometry were discussed. Understanding digital images of PCC pavement surfaces is straightforward—contrast depends only on the ratios of reflectivities of the aggregate materials and the mortar. The values may have to be adjusted to account for wear and weathering of the pavement surface. Understanding crack luminance, however, is much more difficult—small changes in crack geometry or lighting can cause major changes in crack contrast.

In testing automated pavement inspection systems, it is traditional to rely on field tests of the system and to compare with the results obtained by human observers. From looking at digital images of distressed PCC pavements and attempting to generalize luminance measurements based on them, much of the difficulties in past approaches to automated distress evaluation was understood. The fact that under some lighting conditions cracks are more luminous than the surrounding pavement was unexpected; careful measurements of gray levels in digital images of PCC pavements confirmed that cracks illuminated by small bright light sources can appear brighter than, darker than, or identical to the pavement surface. This result violates the basic human intuition that cracks are always dark and demonstrates why image processing algorithms designed for automated pavement inspection must be based on measured video signal values rather than on human notions of crack appearance. That fact leads into the second difficulty with generalizing digital pavement images—the variabilities due to material reflectivities, crack geometry, and lighting make it difficult to characterize crack luminance by merely collecting a large number of crack images. For example, the actual lighting situation is even more complicated than was suggested in the last section in which only a single, small illumination source such as the sun or a lamp was considered. In addition to this direct illumination, cracks usually receive omnidirectional ambient illumination, such as skylight. The ratio of ambient to direct sunlight directly affects the crack luminance. Multiple direct light sources, such as a bank of lamps, will produce even different luminance values. There are many other factors that can alter the crack luminance. It is difficult to imagine that a collection of pavement images, however extensive, can include all of the contrast cases that an inspection system will encounter on the highways. It is not even clear how to select, from a collection of images, the worst case images with which to test automated pavement inspection systems. In other words, exclusive use of unstruc-

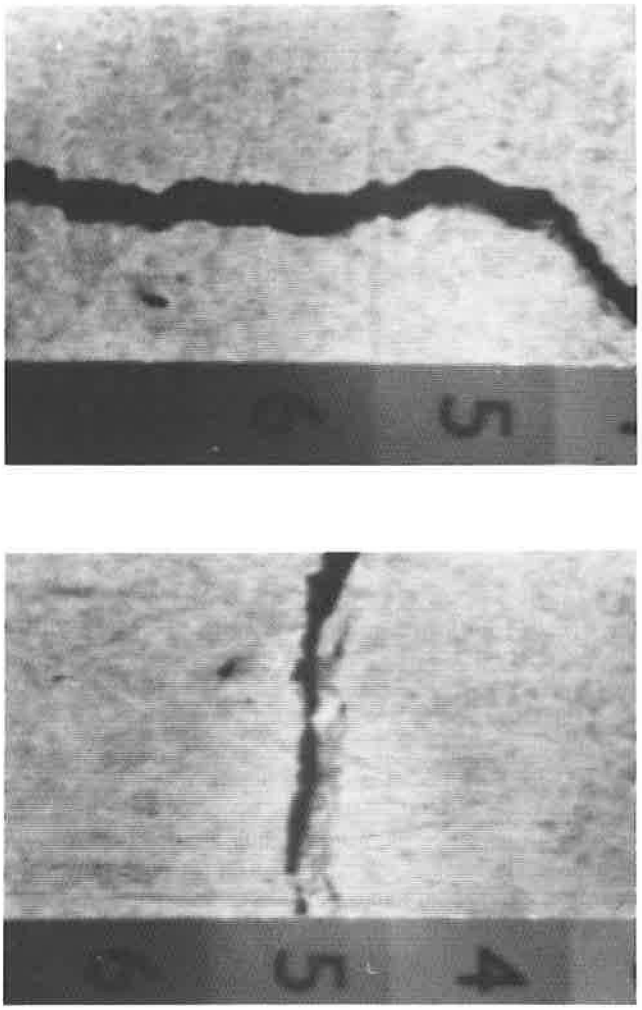

FIGURE 8 Digital images of the pavement sample shown in Figure 7 except that the crack width is 1.5 mm (0.06 in.) (top) illumination crosswise to the crack and (bottom) illumination along the crack.

tured field testing of vision systems is not a good way to validate that the system will work reliably.

In addition to the difficulty of validating system performance, the other problem with using collections of digital pavement images is that it is difficult to generalize an understanding of how to design image acquisition and image processing systems to optimize crack detection. For example, even if the considerable expense and difficulty of obtaining and documenting an exhaustive library of pavement distress images were incurred, the effort would have to be duplicated for all combinations of cameras and other major system components that the system designer might consider using. Similarly, in deciding between natural and artificial lighting, the designer would need images acquired under all possible lighting conditions. This is clearly infeasible.

In this paper, the importance of detailed understanding of crack luminance in designing automated systems for evaluating pavement surface distress has been shown. Although reflectivity measurements of pavement materials can be used to understand the appearance of pavement surfaces, the complexity of the light incidence and reflection that produces luminance inside the cracks defies attempts to generalize an understanding from measuring highway pavement images. As a way around this problem, Wittels and El-Korchi in a companion paper discuss the combination of computer simulations of crack luminance with pavement images as a step in designing and testing automated pavement distress inspection systems.

REFLECTIVITY MEASUREMENTS

This section contains detailed information about the reflectivity measurements. It is presented for the benefit of those requiring detailed knowledge of the methods, but it is placed at the end of the paper so as not to impede the reader who does not need this level of detail.

Pavements are visible because they reflect part of the light they receive. That can be light received directly from the sun or lamps or it can be sun- or lamplight that is reflected by other surfaces. When the surface is a diffuse (or matte) reflector, it obeys Lambert's Law—the luminance of the reflected light is independent of illumination direction and varies cosinusoidally with the viewing angle, measured from the surface normal. This results in an apparent luminance that is independent of viewing angle. The opposite extreme is specular (mirror-like) reflection in which the angle of reflection is equal but opposite to the angle of incidence, relative to the surface normal. Most materials have reflection characteristics between these two extremes and characterizing them can be quite complicated (*31*). Diffuse reflection is the simplest case to model because the surface can be characterized completely by a single reflectivity, a number equal to the ratio of the total light out divided by the total light in, and because the apparent luminance is independent of the viewing angle.

A material's reflectivity can be measured using the reflectometer shown schematically in Figure 9. In this configuration, the light source produces controlled surface illumination and two cameras are used to measure the light reflected. Camera 1 is in line with the illumination and at the same polar angle with respect to the surface normal; it receives both specularly and diffusely reflected light. Camera 2 is at the same polar angle as the illumination, but 90 degrees away in azimuthal angle; it receives only diffusely reflected light. The camera signals are compared during sequential observations of a sample and a diffuse reflectivity standard, MgO; the ratio of the reflectivities is the same as the ratio of the camera signals. This same instrument can be used to verify that a sample reflects diffusely. If the sample is a diffuse reflector, the signals from Camera 1 and Camera 2 will be equal. If it has a specular reflectivity component, Camera 1 will receive substantially more light than Camera 2.

In calculating crack luminances, it is useful to assume that paving materials reflect light diffusely and it is important to validate that assumption. Using the equivalent of a two-camera measurement technique, it was found, with very few exceptions, that the nondiffuse component of reflectivity is less than 0.05 (less than 5 percent of the incident light is reflected specularly) for most paving materials, which is less than the natural variation in total material reflectivities. The most notable exception was feldspar. When used as an aggregate material, the specular reflection from feldspar samples can overwhelm the diffuse reflection under some lighting

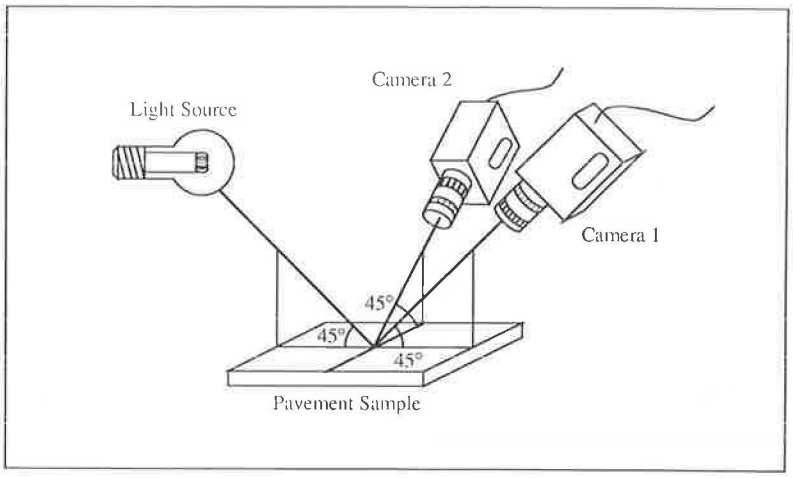

FIGURE 9 Schematic representation of a reflectometer.

conditions. The assumption of diffuse reflection is invalid for wet pavements. It also breaks down on weathered pavements at glancing angles of illumination, as evidenced by the road glare when driving into the sun. That illumination condition produces images that emphasize unimportant variations in surface texture so it would not normally be used for pavement inspection. Therefore, the measurements support the diffuse reflection assumption for most paving materials and most observing conditions.

Figure 9 contains only a schematic representation of a reflectometer. Reflectometer design is beyond the scope of this paper (*17,32*), but there are several important design features that should be incorporated into a reflectometer intended for measuring paving materials. They include the following:

- Illumination and observation angles should match the actual conditions under which the pavement will be viewed by an automated surface distress evaluation system. The solid angle that the camera lens aperture subtends should match that of the automated system's lens. If directed illumination is used, the illumination solid angle should be matched in the reflectometer. These precautions ensure that both systems will measure comparable quantities and will react similarly to pavement materials that produce small specular glints, such as asphaltic pavements.
- The reflectometer light source and sensor should have the same color temperature and spectral sensitivity, respectively, as the automated distress evaluation system. This is to prevent inaccuracies when using the equipment with highly colored paving materials.
- The size of the measured area should be comparable to the minimum crack width to be detected. This ensures that the reflectometer measures local reflectivity variations with size scale comparable to the image acquisition system.

The reflectivity measurements in Figure 4 were made under the following conditions:

- The illumination cone angle was about 0.5 degree, comparable to sunlight. The observation cone angle was about 0.05 degree, comparable to observation with an f/2.8, 5-mm lens. That is the lens that images a 12-ft (3.7-m) wide lane on to a standard 0.35-in. (8.8-mm) video camera sensor when the camera is suspended about 6.8 ft (2 m) above the pavement surface.
- The light source was a 3,200°K tungsten-halogen lamp filtered with a Kodak 80A filter to approximate sunlight and the sensor was a United Detector Corporation model 248 silicon barrier detector with a photometric filter having approximately the spectral response of typical photometrically corrected commercial video cameras.
- A sample area on the order of 0.4 in. (10 mm) in diameter was illuminated and the reflected light measurement was made a spot of diameter 0.08 in. (2 mm) centered in the illuminated area.

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