Integration of Diverse Technologies for Pavement Sensing

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Recognition of the need for good pavement data has resulted in efforts to develop noncontact automated pavement data acquisition systems. These systems collect roughness, geometric, and distress data using a diverse range of sensing technologies. Although many of these technologies are becoming well developed and accepted, there has been a lag in the development of effective methods to exploit the data that is produced. To do this, the diverse technologies used for pavement sensing must be integrated. Currently, integration methods are typically ad hoc and specialized for each application and sensor type. A general method for such integration is described. This general method supports diverse sensors, large datasets, and data abstraction over a wide range, from the location of cracks of a fraction of an inch in width to summary pavement section condition measures. Also, integration requirements are examined, issues of uncertainty are discussed, and examples are presented of pavement sensor data combinations for two diverse application areas. One example integrates video and laser range data to identify pavement cracks. The second example illustrates sensor data integration for pavement condition assessment using three commercial survey systems. Data from these three commercial systems are integrated using the same software model structure and typical summary statistics are derived.

Good pavement data are the foundation of good pavement management (*1*). Recognition of the need for good pavement data has resulted in efforts to develop noncontact automated pavement data acquisition systems. These systems collect roughness, geometric, and distress data using a diverse range of sensing technologies. Although many of these technologies are becoming well developed and accepted, there has been a lag in the development of effective methods to exploit the data that is produced. To do this, the diverse technologies used for pavement sensing must be integrated. Integration requirements are examined, issues of uncertainty are discussed, and examples are presented of pavement sensor data combinations for two diverse application areas.

Integration requirements include a model of the pavement surface into which disparate sensor data can be incorporated. Sensor data must also be registered in the coordinate system that forms the basis of the model, and it must be aligned with data from other sensors. The methods that can be used to ensure good registration and alignment are discussed. Integration also requires surface characterization procedures in which data fusion (or combination) operations perform a key role.

Sources of uncertainty arise from instrument sensing errors, imprecision and slippage in mechanical components, misalignment and registration, data fusion operations, and propagation of error through the aggregation and abstraction involved in the characterization processes of the surface model. Modeling uncertainty is a problem. Methods to reduce error in multisensor systems are briefly discussed and then referenced.

The issues are illustrated with two examples. In one example, laser range and video data are integrated to derive precise maps of routed pavement cracks for a robotic pavement crack filler. This example serves to illustrate the potential of integrating these two sensing technologies for pavement characterization. In the example that follows, a method by which sensor data from existing, commercial, multisensor pavement surveying systems can be integrated in a common pavement surface representation and the advantages that can ensue are illustrated.

A particular pavement surfaces model is used for both applications (*2*). The model is implemented as a software library or "tool kit" using C++, an object-oriented language (*3*). This form of implementation promotes modularity, independence and good data management.

INTEGRATION REQUIREMENTS

Pavement Modeling

The purpose of integrating diverse sensing technologies is to exploit the information available in order to characterize the pavement more effectively. To do this, it is necessary to have a standardized model of pavement surfaces into which many disparate sources of information can be incorporated. The model must also support different levels of data abstraction and aggregation. It must maintain spatial relationships among surface characteristics, it must support automated characterization, and it should support quick access to surface information.

A simple and common model is that based on one dimensional or linear representations of roadways with characteristics indexed by milestone. However, linear models cannot represent information that has width as well as length such as rutting or local areas of distress. Linear representations are therefore incapable of representing many types of scanned data at a low level of aggregation or of maintaining two-dimensional spatial relationships. Many alternative geometric surface models exist that are based on parameterized planar sections (*4–8*). With the exception of Delauney triangles (*9*), none of these models easily supports multiple levels of abstraction and aggregation. None, including Delauney triangles, easily facilitates maintenance of spatial relationships be-

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tween different sources of surface characteristics. The quadtree is an alternative that is symmetric, infinitely decomposable, and easy to construct from pavement sensor data. Quadtrees can also be used to maintain well-defined spatial relationships between different sources of surface data, because the individual quadtrees can be arranged to form parallel structures. A quadtree is a hierarchical, tree-like representation in which a surface is repeatedly divided into square surface areas (quadrants) with finer and finer detail.

A model defined and developed by Haas (*2,10*) makes use of quadtrees. This model serves as a framework to discuss issues of sensor integration. The model (Figure 1) is the combination of a surface representation and the process of developing it. The surface representation comprises characteristics at various levels of abstraction and aggregation. On the basis of this definition, development of the representation is termed "characterization." Characterization includes four basic operations on data: filtering, reduction, fusion, and structuring. Characterization transforms the state of the surface representation. Common data structures support characterization and facilitate the surface representation, and in this way unify the elements of the model.

The model assumes that pavement surfaces are of two and one-half dimensions so that pavement contour information can be included. This assumption implies that pavement surfaces can be represented in a manner analogous to topographic maps without underground elements. Pavement surfaces are represented by characteristics at different levels of aggregation and abstraction. The level of aggregation of a characteristic refers to its spatial extent and its distance hierarchically from original sensed data. Three levels of characteristics are defined:

- Properties—measured directly or derived from other properties,
- Features—derived from properties and other features, and
- Regions—aggregations of sets of features and properties.

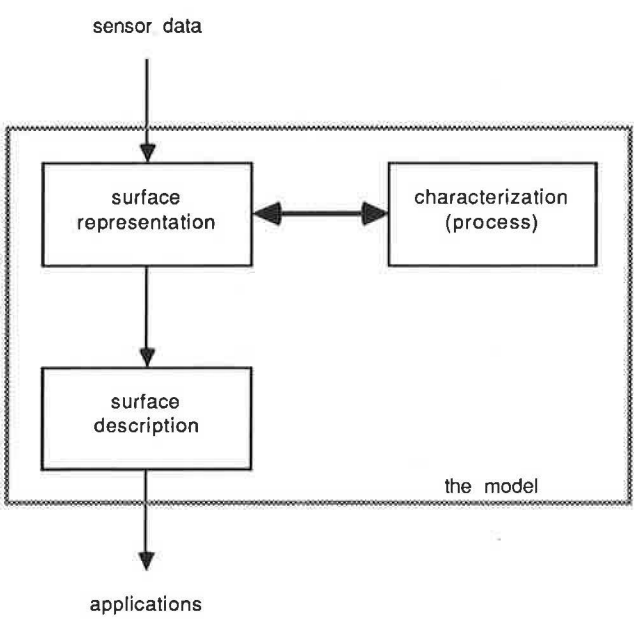

FIGURE 1 Pavement surfaces model.

The surface representation is composed primarily of two data structures. The first is a grid to which sensor data measurements are registered. Measurements from different sensors are referenced to common points on the grid and thereby related to each other spatially. The grid supports sensor data filtering and reduction, and it forms the foundation of a generalized quadtree that is used to relate characteristics in a spatial framework useful for data fusion and structuring. The generalized quadtree has advantages over other surface descriptions. It is compact because of its hierarchical structure and is unified because its nodes create a useful parallelism among surface characteristics, thus maintaining the spatial relationships among the characteristics.

In this model, each node in the generalized quadtree is a data structure, with slots for each surface characteristic in a quadrant and with values for each slot. Descriptions of uniform characteristics spanning a wide area of the surface may be contained in higher nodes and propagated down the tree to access information at any level of detail. For example, Figure 2 shows the quadtree's hierarchical representation of pavement depression and cracking information. In their final state, each quadrant encompasses an area in which the property or feature value is relatively uniform. Quadrants correspond to leaf nodes on the tree, and for any node in the tree its slots may have four states:

- Black—the characteristic fills the area encompassed by the slot's node,
- White—the characteristic is not extant in the area encompassed by the slot's node,
- Grey—the characteristic is to some degree extant in the area encompassed by the slot's node, and
- Undefined—no knowledge is retained concerning the characteristic at this node.

The state of black may have several values. For example, rutting may exist as low, medium, and high. In most cases, it makes sense to discretize continuous-valued properties into a few representative ranges.

Sensor Data Registration and Alignment

Registering sensor data of the surface and aligning it spatially is challenging. A common coordinate system is required in which to sense and register the data and align data from different sources. A cartesian grid can serve this purpose. The grid is an array of points laid out in a rectangular pattern in an *xy* reference plane. The plane is located above the pavement surface, and its orientation is arbitrary. The space between the points along either axis is the same, but the number of points along either axis is variable as well as the magnitude of the space between the points. For the generalized quadtree model, two conditions are imposed. The first is that the number of points in each dimension must be a power of two. The second is that the number of points in each dimension be divisible by a common denominator equal to or one-half the length of the smallest dimension.

The dimensions of the grid should be chosen so that all sensor data can be associated in a one-to-one mapping with points on the grid, which means that no two data from one

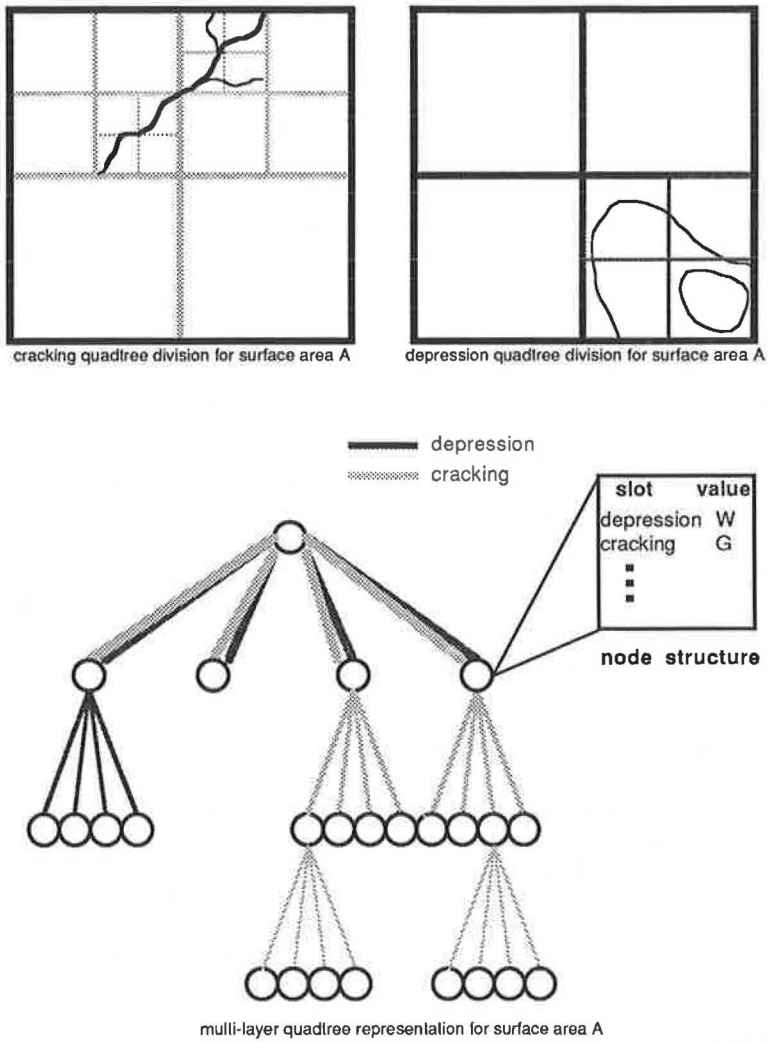

FIGURE 2 Multi-layer surface quadtree.

sensor can be mapped to the same grid point. This condition is satisfied if the data type with the highest spatial resolution is used as a basis for the grid dimensions. The definition of the grid ignores sensor performance in terms of spatial resolution, range resolution, scanner position accuracy, and dynamic range. Instead, these factors could be considered in a measure of variance associated with each sensor. In practice, sensor spatial and range resolutions should be evaluated using good engineering judgment when configuring a sensing system for the task at hand. The grid definition is concerned only with the fact that sensor measurements are centered on points and that these points can be related to a common rectangular grid.

The grid definition also assumes that the aspect ratio of each of the sensors in a multisensor system is identical. The aspect ratio is the ratio of the length to the width of the area sensed. A specialized convolution is required if it is necessary to integrate a laser range scan datum that refers to a square area with a video datum that refers to a 3:4 aspect ratio area.

Although the definition of the grid allows data to be registered that has been acquired via arbitrary sensor scanning patterns, it is preferable to implement raster scan patterns. For the generalized quadtree, the resulting arrays of data should be square with side dimensions equal to a power of two. The data acquired for the robotic pavement crack filler (*11*) is an example. A 2- × 2-m square work area is sensed. The video data is digitized to a resolution of 512 × 512 pixels, and an array of 128 × 128 range values is acquired by the range scanning mechanism; thus each layer of data corresponds to and is converted at different levels of the generalized quadtree. Registration is simple with such data, although alignment may be difficult. Calibrating and maintaining alignment between different scanning mechanisms assuming one or the other forms the reference coordinate system is challenging but feasible in practice. For example, the Komatsu pavement surveying system uses a single argon laser line illuminator that is scanned by two different receiving mechanisms, one to develop an image from which cracking

data are acquired automatically and one to develop a transverse profile from which rutting data are acquired automatically. Because all these mechanisms are coordinated by the same system clock, the acquired data can theoretically be precisely aligned and registered.

Surface Characterization

Characterization changes the state of the surface representation to produce a useful description of the surface. The four basic operations in characterization can be defined as

1. Data filtering—linear and nonlinear transformations,
2. Data reduction—deriving a representative value from a set of data,
3. Data fusion—combining two or more spatially concurrent datums into a new datum, and
4. Data structuring—linking and integrating data.

Computer processing and space constraints along with the nature of the application affect how the balance of these operations are divided between the grid and the generalized quadtree. Data filtering and reduction are performed most effectively on grid data, and data fusion and structuring are performed most effectively on the generalized quadtree.

As an example, suppose one wished to extract the feature fatigue cracking using the characteristics of rutting, strength, and cracking from a generalized quadtree model. This information can be acquired in raw form as property data using range, deflection, and vision sensors, respectively, and reported in arrays of data mapped onto points on the grid. The grid data are processed and then converted at appropriate levels of aggregation to the generalized quadtree representation. Conversion is a structuring operation that places the properties in the generalized quadtree as slot values in node data structures. The slot values are datums that are combined by a feature extraction algorithm composed of set operations into datums in a new slot that represents fatigue cracking. This process is data fusion. The structure of the generalized quadtree relates the fatigue cracking feature spatially to the other characteristics and to the pavement surface.

Following this example, the characterization operations can be grouped into several practical classes. The first includes operations on the grid to prepare raw sensor data for conversion to the generalized quadtree. The next includes operations to convert grid data to the quadtree representation. Quadtree set operations form one class, and adjacency and region labeling another. These classes of operations are described in the following paragraphs.

The objective of grid data processing is to prepare raw sensor data for conversion to a general model. It should result in each datum indicating with as high a degree of confidence as possible the existence or nonexistence of a characteristic in a specific area. Aggregation is useful because the subsequent conversion operation is costly. Reduced data must be arranged in an array format with the same row:column ratio as the underlying grid and with dimensions equal to the grid dimensions divided by two to a power.

Filtering is used to segment grid data and to extract features (*5,12*). Thresholding and edge detection are examples. Edge detection has been used on video image data of pavement surfaces to segment datums possibly located along cracks because cracks form an edge between regions in an image (*13*). Skeletonizing is an operation that derives the skeletons of blobs in a black and white image. It is one method of reducing data. Another is to divide the grid into areas corresponding to quadrants at some arbitrary level of aggregation and derive a summary statistic for each area. Several distinct conversion operations are necessary to convert grid data to the generalized quadtree representation including grafting layers of grid data onto an existing quadtree structure. Conversion from generalized quadtree data to raster data is also required to display and print graphic results. The pavement surface model's software library implements all of these operations. The model also implements two binary set operations, union and intersection, from which more complex set operations can be constructed (Figure 3).

Identifying and labeling regions is useful for a number of applications. For example, individual routed cracks and potholes form regions on the surface and must be identified for automated filling operations. Areas of patching or a particular type of degradation such as edge cracking are worth labeling for maintenance calculations or deterioration studies. Regions can be identified and labeled using a series of set operations and connected component labeling. For example, the intersection of alligator cracking and severe rutting in the wheel paths can be constructed in a target slot, then connected component labeling can be applied to the target slot to identify contiguous areas of the cracking-rutting set. Of course, regions can be formed from a single characteristic, in which case connected component labeling is used directly on the characteristic's slot.

The generalized quadtree can be encoded and stored in files forming an inventory data base. The files can be managed and accessed using a relational data base management system. With the use of indexing and the relational data base, the data can be accessed by pavement section, local area, surface property, surface feature, and different levels of aggregation and abstraction. Information from within a stored pavement section is retrieved by first reconstructing the section. The section is deconstructed when it is no longer needed.

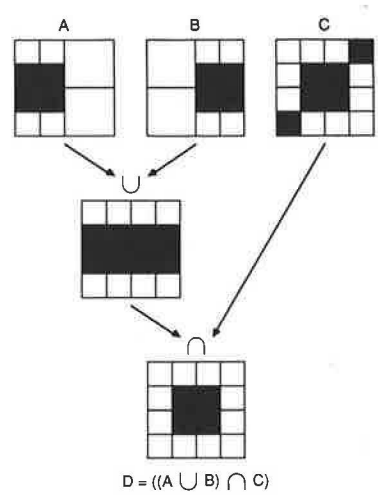

FIGURE 3 Set operations.

SOURCES OF UNCERTAINTY

Sources of uncertainty arise from instrument sensing errors, imprecision and slippage in mechanical components, misalignment and registration, data fusion operations, and propagation of error through the aggregation and abstraction involved in the surface model's characterization processes. Sensing errors can sometimes be ameliorated with more sophisticated technology such as an infrared range finder with built-in automatic gain control. For imaging, increased precision and reduced exposure time can be achieved with special video cameras and lighting. In both these cases, there is a clear trade-off between cost and quality of data. In most cases, some error is acceptable and unavoidable.

Incorrect registration of data can occur because the scanning mechanism exhibits mechanical imprecision and position feedback is not adequate. In a work system such as a robotic pavement maintenance machine, there is potential for error because of vibrations and relative shift between different sensors. Also, environmental factors such as dust, wind, heat, shadows, and even noise can affect sensor performance. Ultrasonic range sensors are especially sensitive to many of these factors.

Misalignment of scans results when the different sensing systems are not rigidly connected to each other, when the areas scanned are not precisely the same dimensions in terms of their outer boundaries, or when there are timing irregularities. In laboratory experiments, the first two problems can be reduced by clearly marking the boundaries of the test scene and adjusting scanning mechanisms to those boundaries. In practice, the scanning systems can be engineered for alignment, but there will always be some error. Alignment error can also be the result of cumulative round off errors in control algorithms.

The sources of error discussed so far are impossible to eliminate, and difficult to compensate for or to model (*14,15*). The generalized quadtree and a few other geometric models provide mechanisms for handling some types of uncertainty in the form of their ability to work at different levels of aggregation with confidence measures associated with characteristics. There has been significant research in the areas of modeling and reducing sensor error in robotic and automated sensing systems. For instance, methods for reducing error have been developed that fuse data from multiple time and position displaced scans and from multiple sensors. There is a large body of literature in this area (*4,16–27*). However, it is probably not practical for pavement surveying and automated pavement work tasks to make multiple scans with the same sensor of the same general surface area, because time does not permit such redundancy in a commercial system. Changing position will likely not create any useful new perspectives either given the generally two-dimensional nature of the surface unless precise stereo vision processing is applied. However, modeling uncertainty within the context of a pavement surfaces model is worthy of further investigation.

EXAMPLE APPLICATION: LASER RANGE AND VIDEO DATA COMBINATION FOR PAVEMENT CRACK IDENTIFICATION

Identifying cracks in the road surface automatically is not an easy problem (*13,28–33*). Mapping the layout of the cracks in detail and selecting those to be filled increases the difficulty. However, automatic crack mapping is a critical step in an automated pavement crack filling system (*11*), and this system is followed as an example in this section. In the case of routed cracks, the identification problem is simplified by distinct visual patterns of debris and by consistent groove dimensions. To identify the cracks, characteristic surface data are required. Applicable sensing technology includes vision, range, and forward-looking infrared devices. In practice, all these sensors experience noise because of the varied topological and color conditions of the pavement surface, and because of environmental factors such as wind and sunlight. Even with good data, a crack identification system can be fooled. Analysis of a video image alone indicates that it is almost impossible to automatically detect the difference between a routed crack, a filled crack, and a strip of dark oil. However, with the corroboration of range information, the routed crack can be distinguished from the imposters. Conversely, range data alone are too noisy to build a good crack representation by themselves, their sensitivity range is narrow, and they are time consuming to collect. Instead, combining information from multiple sources in a common surface representation can increase the overall accuracy and speed of crack perception.

A possible first step in routed crack mapping is to acquire a digitized video image of the area of pavement (Figure 4). The image is segmented by binarizing it (Figure 5). This means that pixels with a grey level value below a threshold value are labeled black, and those with greater or equal values are labeled white. The threshold is set automatically but manually tuned for the local pavement section conditions. The next step is to remove noise from the resulting binary image. This is done using a simple erosion procedure implemented using a convolution operator. The resulting image still includes many objects that are not cracks (Figure 6).

To build a traversal plan for later crack-filling operations of those objects that are eventually determined to be cracks, ordered lists of coordinate pairs along their central axes must be derived. Strings of pixels can serve as ordered lists of

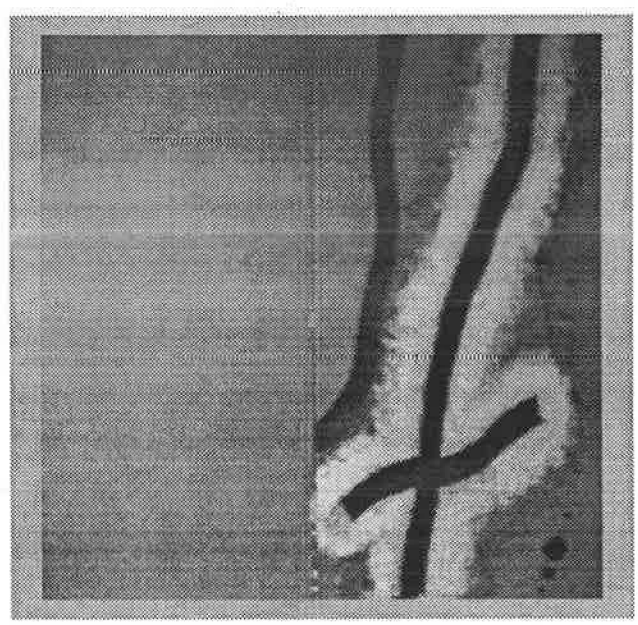

FIGURE 4 Video data of test scene.

FIGURE 5 Binarized video data of test scene.

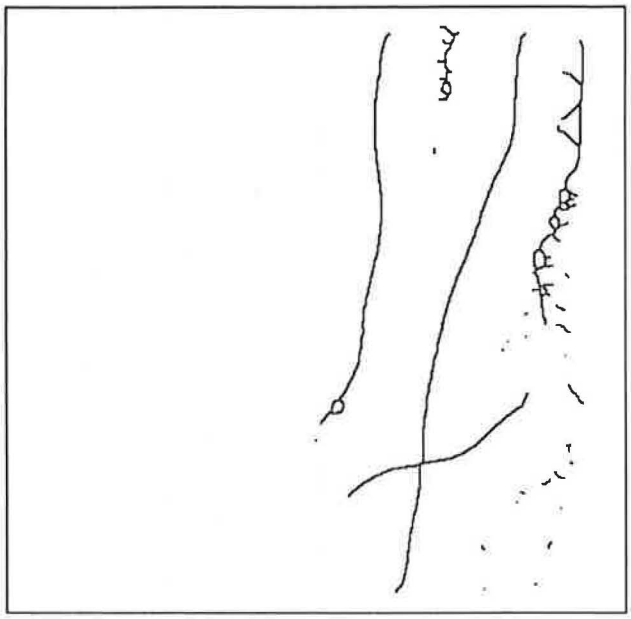

FIGURE 7 Skeletonized video data of test scene.

FIGURE 6 Filtered video data of test scene.

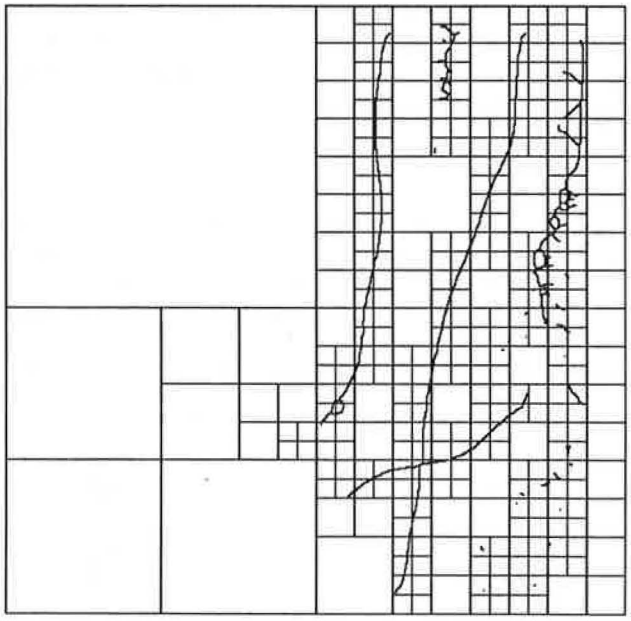

FIGURE 8 Quadrant divisions for video data of test scene.

coordinates. In order to derive these strings, an algorithm that thins image objects to something that resembles their skeleton can be used (*34,35*) (Figure 7).

The skeletonized image is still in grid data format. At this point, it is converted to the multilayer quadtree representation filling the raw image data slot. Because the grid data are an array of 512 × 512 pixels, the resulting tree is up to nine levels deep. Figure 8 shows the quadrant divisions down six levels overlaid on the binary video data. Each image object is then identified, labeled, and sized. Both these procedures are implemented using the model's software library.

Figure 8 indicates that many spurious objects will still exist in the surface representation at this point. Many of the objects can simply be removed on the basis of a size threshold. A library function is used to traverse the tree and prune those branches corresponding to objects below the threshold size (Figure 9). The result is that both the tree size (computer memory used) and the work required for subsequent algorithms are reduced.

One of the purposes of integrating the video data into the multilayer quadtree first is to use it to determine areas of interest in the scene. Areas are interesting if there are vision objects in them. Time is saved in the overall crack-filling cycle by range scanning only the areas of interest, because range scanning is a time-consuming operation. It requires physical traversal of the scene using an *xy*-table. The quadtree is a

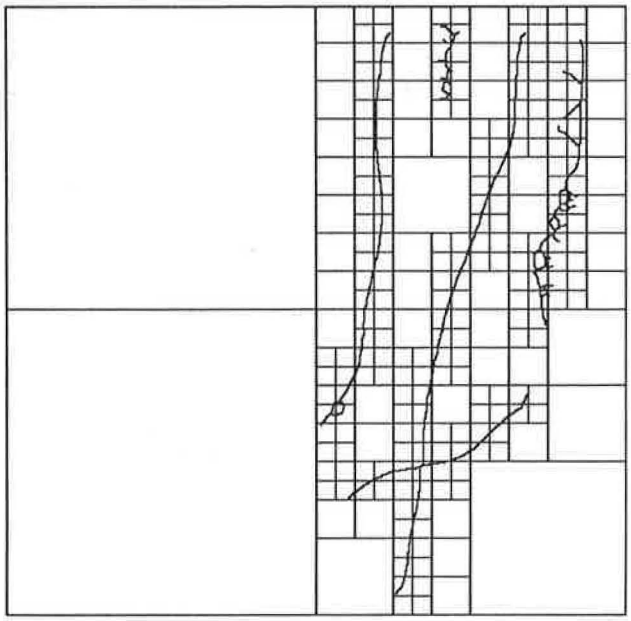

FIGURE 9 Video object pruning results for test scene.

useful tool for breaking down the scene into areas of interest that should be range scanned. Traversal of the quadtree down to a minimum level of aggregation will yield white quadrants that should not be scanned and grey and black quadrants that should be scanned. This pattern is passed to the range-scanning subsystem, which acquires range data for the darkened areas.

Processed range data can be grafted onto the multilayer quadtree using the library function for that operation (Figure 10). The range information is then used to corroborate or dismiss the vision objects. The percentage intersection of range black quadrants with each vision object is calculated. Vision objects with corroborating range data above a threshold percentage are retained while those below are removed from the quadtree. The remaining objects are considered the best estimate of the existence of cracking (Figure 11). An alternate approach to identifying routed cracks would have executed a pure intersection operation on raw vision and range information after both were incorporated in the multilayer quadtree. Then connected component labeling would be applied to the result of the intersection operation. Although this could have been done with library functions alone, the advantage of the connectivity of the vision data might be lost. That is, the vision objects that do correspond to cracks represent them well, and there is no point breaking them up with noisy range data.

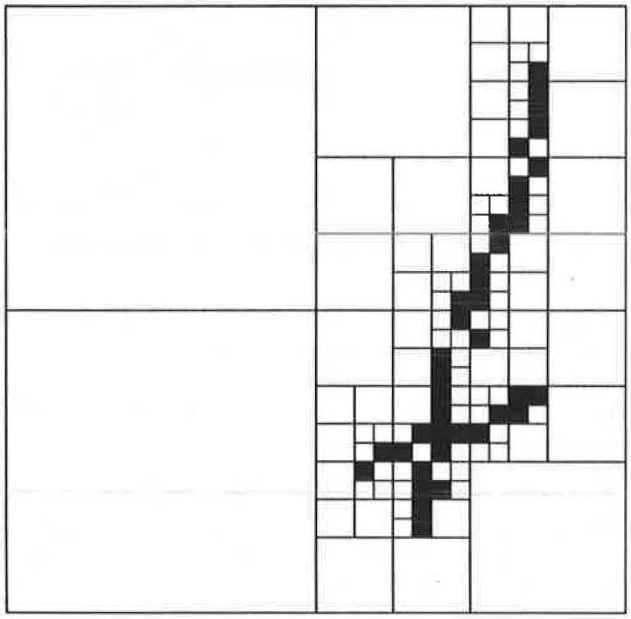

FIGURE 10 Quadrant divisions for processed range data of test scene.

AN EXAMPLE APPLICATION: MULTIPURPOSE SURVEY SYSTEM DATA COMBINATION

Several commercial, multipurpose pavement condition survey systems have been developed in recent years. Their purpose is to collect surface condition information to characterize the performance of pavements. To date, the data have been processed in an ad hoc and narrowly focused manner. It is possible to take greater advantage of the data by integrating it more effectively. Although no general surface representation exists that provides an automated, common link between the pavement condition surveying systems and reporting systems, the pavement surfaces model described earlier can act as this link. Surface features like cracking, rutting, roughness, and strength can be integrated in the model's surface representation and reported at any degree of aggregation and several levels of abstraction. Further characterization of the representation results in additional useful feature and region information. The model can also be used to calculate aggregate pavement condition indexes for whole sections of pavement.

These advantages are illustrated by integrating data from three different pavement surface condition data acquisition

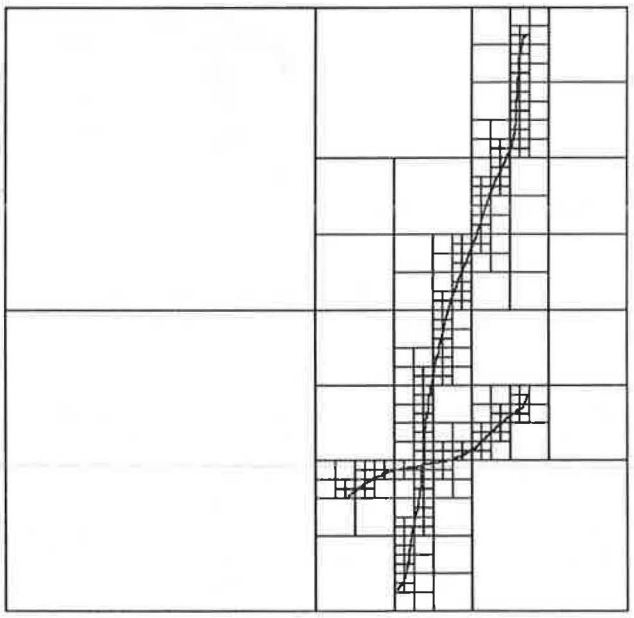

FIGURE 11 Confirmed routed crack object for test scene.

systems into the model's surface representation and calculating the pavement condition index (PCI) for each subsection represented. The acquisition systems include: (a) Komatsu Ltd.'s Automatic Pavement Distress Survey System (*29*), (b) Roadman-PCES Inc.'s Pavement Distress Imager-1 (*28*), and (c) PASCO USA Inc.'s RoadRecon survey system.

Komatsu's survey system (Figure 12) acquires aligned cracking, rutting, and roughness data concurrently at up to 40 mph. The rutting and roughness data are processed in real time. The roughness measure is based on slope differential values derived from a linear array of three laser range sensors. An image analysis subsystem processes image data at a rate up to 450 m/hr or about 0.25 mph, and can process the data on board. The imaging system uses argon laser irradiation of a 1-mm-thick strip in front of the vehicle, 4 m wide. The strip is scanned using a photomultiplier tube and the resulting image data are normally stored on a high-density videotape recorder device for later laboratory-based computer processing and analysis. The processing system uses a parallel-processing architecture to implement an algorithm that is reportedly capable of identifying width, length, and direction of cracks, and of identifying type of cracking within 0.5-m-square sections. Compared with hand digitization of cracks on a view screen, the system is estimated to perform at 80 percent of the accuracy of manual identification.

The PCES Pavement Distress Imager I is an on-board, real time pavement imaging system. It uses intense illumination and fast-exposure CCD line cameras to acquire image data line by line, and completely process it as the vehicle moves down the road at speeds up to 50 to 60 mph. Possible gross changes in surface texture and color are flagged automatically, while manual flagging is used for other artifacts such as patching. The system covers 33 percent of a 12-ft-wide pavement surface, thus it may not observe progressive edge cracking. However, the system can produce an estimate of the existence of cracking in each 1.5-in.-square section covered, on the basis of a count of the number of black pixels left in the square after thresholding.

The PASCO USA system acquires film of the pavement surface with a high-speed vertically oriented camera while traveling at highway speeds. The film is later analyzed in a laboratory setting for surface distress conditions. Distress conditions are identified manually; however, the process is partially automated with the aid of a film motion analyzer, which

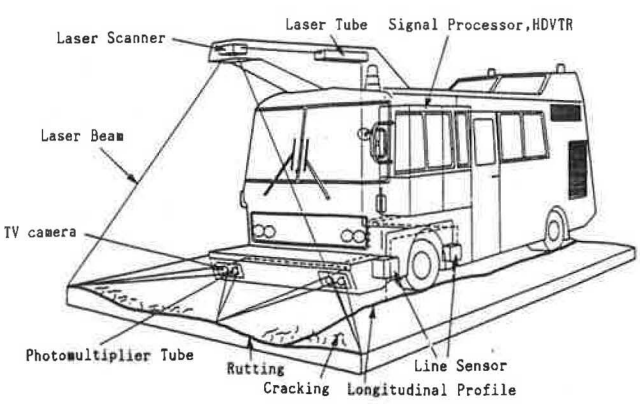

FIGURE 12 Komatsu Ltd.—Automatic Pavement Distress Survey System.

displays and advances film on a frame-by-frame basis. Depending on the lane width, each frame is lined off in a 12- × 12-ft or 12- × 16-ft basic grid for recording purposes. Much of the basic cracking data acquisition could be automated, perhaps enhancing the productivity of the process described. The PASCO USA system also acquires transverse profile data at intervals along the pavement from which rutting information is derived. The rutting data are registered in the same grid system as the surface distress data.

Data samples were acquired from each of the three sources. To prepare it for incorporation in the generalized quadtree representation, the data from each source were translated from their original storage format to one suitable for conversion to the strip quadtree structure. Komatsu provided cracking, rutting, and roughness data for three 4- × 100-m subsections. The rutting data were reported for each wheel path every 25 cm. It was averaged over 2 m for every level-one quadrant in the strip tree. Roughness was reported every 10 m. It was prepared for conversion at the first level in the quadtree. Cracking data were reported for every 0.5- × 0.5-m quadrant and were rearranged to prepare them for conversion at level three of the strip quadtree. The transverse profile data from which the rutting data were derived could potentially, with further computer analysis, yield data on the existence and frequency of potholes.

PCES provided cracking data for an 8- × 176-ft subsection. Each 8- × 8-ft area is digitized at a resolution of 1,024 × 1,024 pixels. Cracking data are reported for each 16- × 16-pixel square or 1.5- × 1.5-in. tile. Each tile has either a black state equal to 1 or a white state equal to 255. The data were prepared in order to build two 8- × 64-ft sections. Although the original pixel data would form a quadtree with 10 levels, the data were converted at the tile aggregate level to create a strip quadtree six levels deep.

PASCO USA provided general surface distress data for a section of pavement 1,650 ft long and 12 ft wide. Rutting data were reported at stations every 250 ft. A 400-ft subsection at the beginning of the section was selected for conversion. Each cell in the basic grid can contain several distress codes, so each distress type was incorporated into the strip quadtree in a separate layer including the rutting data. Certain types of distress cannot overlap. Groups of such mutually exclusive types can be incorporated in the quadtree using a single layer for each group and a separate black state for each type in the group. Longitudinal and transverse cracking might form such a group, but it is clearly the judgment of PASCO USA that both types of cracking might exist in a single square foot. The concurrency of a type of cracking and patching in the PASCO USA data indicate cracking that has been patched or filled. With its set functions the model can make use of this information in order to indicate stripping of patching or progression of cracking since repair. Such progression may indicate deterioration. Four columns of blank data were added to the PASCO USA data to prepare them for conversion. This would not be necessary for the 16-ft-wide sections. For percent-area-covered calculations, the padding described must be taken into account. The PASCO USA source data format included provision for severity values for distress types; however, the data file used did not include this information.

Each layer of the PASCO USA subsection is shown in Figure 13, including patching, alligator cracking, longitudinal

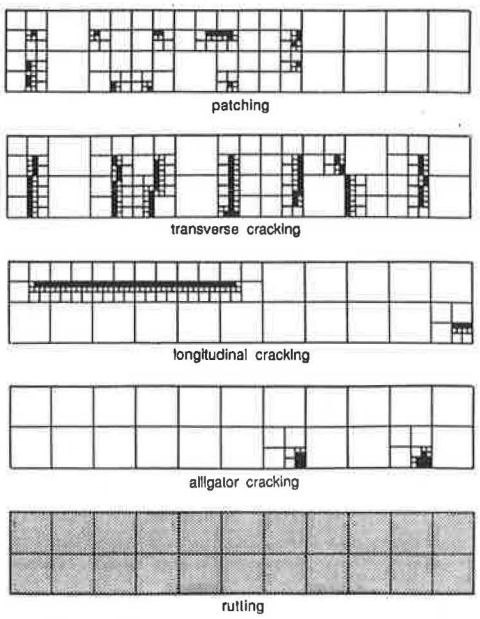

FIGURE 13 PASCO USA quadtree layers.

cracking, transverse cracking, and rutting. Only the first 10 roots have been converted, corresponding to the first 80 ft along the subsection. Figure 14 shows the intersection of transverse cracking and patching for the PASCO USA subsection in the first strip and simply transverse cracking in the second strip. Separating areas of different or overlapping distress types could be useful for pavement deterioration modeling. If accurately aligned, time-separated surveys of the same surface could be incorporated in the model's representation and used to graphically illustrate the process of deterioration as well as accurately assessing its extent at each stage. The previous section on integrating range and vision data demonstrates how the acquisition of cracking and patched cracking data could be automated.

Calculating the PCI for the Komatsu and PASCO USA subsections is made possible with the use of the tools the model provides. A distinction is made in the PAVER guide (*36*) between linear and spatial measures for different distress types. For example, longitudinal and transverse cracking are measured in linear feet while alligator cracking is measured in square feet. Using the model's area functions for both is generally acceptable, because cracking running through a 1-ft^2 area is approximately 1 ft long. None of the cracking data provided were classified according to severity. To include severity information in the surface representation, each severity level can be represented as a different black state for each layer of cracking data. This approach is used for the rutting data in the sample subsections. To calculate the PCI, the cracking data are assumed to be moderate in severity.

The PCI deduct values for each Komatsu subsection are presented in Table 1. The resulting PCI values are 40, 30, and 19, respectively. If the average rut width is reduced to 1 ft, the PCI value for the first subsection improves to 53. The PCI deduct values for the PASCO USA subsection are presented in Table 2. Its PCI value is 27.

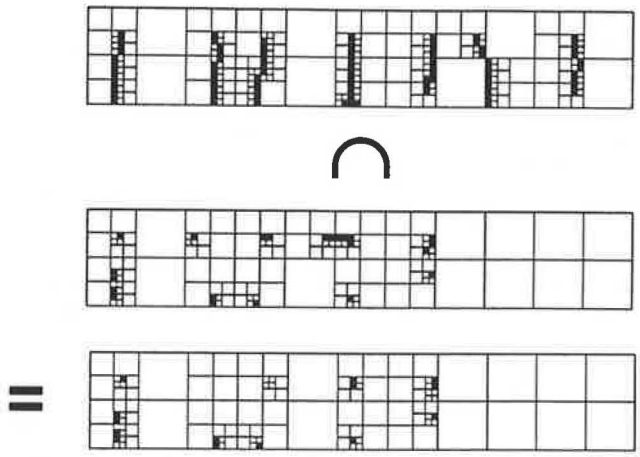

FIGURE 14 PCES transverse cracking and patching.

CONCLUSIONS

The requirements of effective sensor data integration suggest that a formal, spatial model of pavement condition would be of considerable benefit. With a formal model, general functions can be applied for sensor registration, alignment, and fusion. Data combination and summary at different levels of integration are facilitated. Integration to yield detailed maps of surfaces at a scale of fractions of inches and data management for various kinds of sensors on large pavement sections have been described. Because of the generality of the underlying model, these different applications used the same software.

The research suggests that an open architecture for pavement representation and management is possible. In this open architecture, condition assessment data obtained from different commercial systems and at different points in time may be integrated. Graphic displays similar to geographic information systems (GISs) and utilities for producing summary reports can be provided in this system. Different management and analysis systems such as PAVER can be integrated with the information management system. At the heart of this open architecture would be a data model representing the pavement condition in an organized fashion.

REFERENCES

1. R. Haas, W. R. Hudson, and C. A. V. Quieroz. A Strategic Approach to Pavement Rehabilitation Data Needs. Presented at 2nd International Symposium on Pavement Evaluation and Overlay Design, Rio de Janeiro, Brazil, 1990, (in process).
2. C. Haas. *A Model of Pavement Surfaces*. Ph.D. dissertation, Carnegie Mellon University, Pittsburgh, Pa., Sept. 1990.
3. C. Haas. *Generalized Quadtree Library (GQL) Software Development Guide*. Technical Report R90-190, Department of Civil Engineering, Carnegie Mellon University, Pittsburgh, Pa., 1990.
4. P. Allen. *Surface Descriptions From Vision and Touch*. IEEE 1984 International Conference on Robotics, Computer Society Press, Washington, D.C., 1984, p. 394.
5. D. H. Ballard and C. M. Brown. *Computer Vision*, Prentice-Hall Inc., Englewood Cliffs, N.J., 1982.
6. Y. P. Hung, D. B. Cooper, and B. Cernuschi-Frias. Bayesian

TABLE 1 KOMATSU PCIs

Subsection 1			
Distress Type	Density	Severity	Deduct Value
Longitudinal Cracking	0.11	M	0
Transverse Cracking	0.00	M	0
Rutting	16.15	L	32
Rutting	8.23	M	41
Rutting	0.16	H	22

Subsection 2			
Distress Type	Density	Severity	Deduct Value
Longitudinal Cracking	0.29	M	2
Transverse Cracking	0.50	M	4
Rutting	12.81	L	30
Rutting	14.34	M	50
Rutting	0.92	H	26

Subsection 3			
Distress Type	Density	Severity	Deduct Value
Longitudinal Cracking	3.78	M	19
Transverse Cracking	2.14	M	14
Rutting	7.32	L	24
Rutting	16.78	M	52
Rutting	6.10	H	51

TABLE 2 PASCO PCI

Subsection 1			
Distress Type	Density	Severity	Deduct Value
Alligator Cracking	1.33	M	24
Transverse Cracking	5.63	M	23
Longitudinal Cracking	6.25	M	24
Rutting	27.08	L	57

Estimation of 3-D Surfaces from a Sequence of Images. *Robotics and Automation—Proc., 1988 IEEE Conference*, Computer Society Press, Washington, D.C., April 1988, pp. 906–911.

7. J. Ponce and M. Brady. Toward a Primal Surface Sketch. *Robotics*, Civil Engineering course literature, Carnegie Mellon University, Pittsburgh, Pa., 1985.
8. C. Thorpe and T. Kanade. *1987 Year End Report For Road Following at Carnegie Mellon*. Technical Report CMU-RI-TR-88-4, Robotics Institute, Carnegie Mellon University, Pittsburgh, Pa., April 1988.
9. J. Boissonnat and M. Teillaud. *An Hierarchical Representation of Objects*: The Delaunay Tree, Technical Report 0-89791-194-6/86/0600/0260, Association for Computing Machinery, New York, N.Y., 1986.
10. C. Haas and C. Hendrickson. Computer-Based Model of Pavement Surfaces. In *Transportation Research Record 1260*, TRB, National Research Council, Washington, D.C., 1990.
11. C. Haas, C. Hendrickson, and S. McNeil. *A Design for Automated Pavement Crack Filling*. Technical Report, Department of Civil Engineering, Carnegie Mellon University, Pittsburgh, Pa., Aug. 1990.
12. K. R. Castleman. *Digital Image Processing, Signal Processing Series*, Prentice-Hall, Englewood Cliffs, N.J., 1979.
13. C. Haas, H. Shen, and R. Haas. Application of Image Analysis Technology to Automation of Pavement Condition Surveys. *Proc., International Transport Congress*, Montreal, Canada, Sept., 1984.
14. F. Humplick. *Error Analysis of Optical Techniques for Pavement Surface Distress Evaluation*. Working Paper, Massachusetts Institute of Technology, Cambridge, 1987.
15. S. McNeil and F. Humplick. Evaluation of Errors in Pavement Surface Distress Data Acquisition. *Proc., 1st International Conference on Applications of Advanced Technology to Transportation*, Hendrickson and Sinha, eds., Purdue University, West Lafayette, Ind., Feb. 1989.
16. H. F. Durrant-Whyte. Sensor Models and Multi-Sensor Integration. *Spatial Reasoning and Multi-Sensor Fusion: Proc., 1987 Workshop*, Morgan Kaufmann Publishers, Inc., Los Altos, Calif., Oct. 1987, pp. 303–312.
17. H. F. Durrant-Whyte. Consistent Integration and Propagation of Disparate Sensor Observations. *Robotics and Automation—Proc., 1986 IEEE Conference*, Computer Society Press, Washington, D.C., 1986, p. 1464.
18. A. Elfes and L. Matthies. Integration of Sonar and Stereo Range Data Using a Grid Based Representation. *Robotics and Automation—Proc., 1988 IEEE Conference*, Computer Society Press, Washington, D.C., April 1988, p. 727.
19. J. S. Duncan and L. H. Staib. Shape Determination from Incomplete and Noisy Multisensor Imagery. Spatial Reasoning and Multi-Sensor Fusion—Proc., 1987 Workshop, Morgan Kaufmann Publishers, Inc., Los Altos, Calif., Oct. 1987, p. 334.
20. J. S. Duncan, J. R. Gindi, and K. S. Narendra. Low Level Information Fusion: Multisensor Scene Segmentation Using Learning Automata. *Spatial Reasoning and Multi-Sensor Fusion—Proc., 1987 Workshop*, Morgan Kaufmann Publishers, Inc., Los Altos, Calif., Oct. 1987, p. 323.
21. O. D. Faugeras, N. Ayache, B. Faverjon, and F. Lustman. Building Visual Maps By Combining Noisy Stereo Measurements. *Robotics and Automation—Proc., 1986 IEEE Confer-*

ence, Computer Society Press, Washington, D.C., 1986, p. 1433.
22. R. C. Luo and M. H. Lin. Robot Multisensor Fusion and Integration: Optimum Estimation of Fused Sensor Data. *Robotics and Automation—Proc., 1988 IEEE Conference*, Computer Society Press, Washington, D.C., April 1988, p. 1076.
23. S. L. Chiu, D. J. Morley, and J. F. Martin. Sensor Data Fusion on a Parallel Processor. *Robotics and Automation—Proc., 1986 IEEE Conference*, Computer Society Press, Washington, D.C., 1986, p. 1629.
24. J. L. Crowley and F. Ramparany. Mathematical Tools for Representing Uncertainty in Perception. *Spatial Reasoning and Multi-Sensor Fusion—Proc., 1987 Workshop*, A. Kak and S. Chen, eds., Morgan Kaufmann Publishers, Inc., Los Altos, Calif., Oct. 1987, p. 293.
25. T. L. Huntsberger and S. N. Jayaramamurthy. A Framework for Multi-Sensor Fusion in the Presence of Uncertainty. *Spatial Reasoning and Multi-Sensor Fusion—Proc., 1987 Workshop*, A. Kak and S. Chen, eds., Morgan Kaufmann Publishers, Inc., Los Altos, Calif., Oct. 1987.
26. *A Report on the Workshop on Multisensor Integration in Manufacturing Automation*. T. C. Henderson, P. Allen, I. Cox, A. Mitiche, H. Durrant-Whyte, and W. Snyder, eds. National Science Foundation, 1987.
27. J. M. Richardson, K. A. Marsh, and J. F. Martin. Techniques of Multisensor Signal Processing and Their Application to the Combining of Vision and Acoustical Data. *Proc., 4th International Conference on Robot Vision and Sensory Controls*, Institute of Electrical and Electronic Engineers, Inc., New York, N.Y., Oct. 1984.
28. B. C. Butler, Jr. Pavement Surface Distress Segmentation Using Real Time Imaging. *Proc., 1st International Conference on Applications of Advanced Technology to Transportation*. C. T. Hendrickson and K. Sinha, ed. ASCE, New York, Feb. 1989.
29. T. Fukuhara, K. Terada, M. Nagao, A. Kasahara, and S. Ichihashi. Automatic Pavement-Distress-Survey System. *Transportation Engineering*, Vol. 116, No. 3, 1990, pp. 280–286.
30. L. C. Bomar, W. F. Horne, D. R. Brown, and J. L. Smart. *A Method to Determine Deteriorated Areas in Portland Cement Concrete Pavements*. Technical Report, Gulf Applied Research, Electromagnetics Facility, Marietta, Ga., Jan. 1988.
31. K. R. Maser. *Computational Techniques for Automating Visual Inspection*. Center for Construction Research and Education, Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, 1987.
32. D. H. Mendelsohn. Automated Pavement Crack Detection: An Assessment of Leading Technologies. Proc., 2nd North American Conference on Managing Pavements, FHWA, U.S. Department of Transportation, Nov. 1987, p. 3.297.
33. M. Wigan and M. C. Cullinan. *Image Processing Applied to Roads: Surface Texture, Mensuration, Vehicle Shape and Number Detection*. Special Report 145, Australian Road Research Board, Vermont South, Victoria, Jan. 1987.
34. T. Y. Zhang and C. Y. Suen. A Fast Parallel Algorithm for Thinning Digital Patterns. *Communications of the Association of Computer Machinery*, Vol. 27, No. 3, March 1984, pp. 236–239.
35. H. E. Lu and P. S. P. Wang. A Comment on "A Fast Parallel Algorithm for Thinning Digital Patterns." *Communications of the Association for Computing Machinery*, Vol. 29, No. 3, March 1986, pp. 239–242.
36. M. Y. Shahin and S. D. Kohn. *Pavement Maintenance Management for Roads and Parking Lots*. Technical Report CERL-TR-M-294, U.S. Army Construction Engineering and Research Laboratory, Champaign, Ill., Oct. 1981.

Publication of this paper sponsored by Committee on Applications of Emerging Technology.