A stereometric knowledge-based system for maintenance of street networks

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A stereometric knowledge-based system for maintenance of street networks[1]

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Abstract: The main objective of this work was to investigate the potential of integrating a stereometric vision system, i.e., using digital stereo images, and a knowledge-based system for flexible pavement distress classification. Classification process includes distress type, severity level, and options for repair. A hybrid stereo vision and knowledge-based system (called K-PAVER) was developed. The system extracts distress measurements using a PC-based stereo vision system. Geometric surface measurements such as point locations, distances, areas, volumes, and surface areas could also be computed. The knowledge-based system developed utilizes a set of if...then rules from the PAVER system (a pavement maintenance management system for roads and streets) and related literatures. New parameters, including shape parameters, orientation, and some geometrical measurements, were introduced to the system in order to facilitate the distress classification process. A criterion for maintenance priorities based on four parameters was developed. These parameters are pavement condition index, average daily traffic, location of distressed pavement, and street class. Surface measurements and automatic classification decision-making were validated and tested for all distress types. The developed system gives accurate results in both the measurement mode and the decision-making phase. This result opens the door for a fully automated distress classification process without any human intervention.

Key words: knowledge-based systems, vision systems, stereo measurements, flexible pavement distresses, maintenance priorities, pavement maintenance management systems.

Résumé : L'objectif principal de cette recherche est d'étudier le potentiel d'intégration d'un système de vision stéréométrique, i.e., utiliser des images stéréos digitales, et un système à base de connaissances dans le but de classifier les détériorations des revêtements souples. Le processus de classification inclut le type de détérioration, le niveau de sévérité et les options de réfection. Un système à base de connaissances utilisant la vision stéréo hybride (nommé K-PAVER) fut développé. Le système quantifie les détériorations au moyen d'un système de vision stéréo sur PC. Des mesures de surfaces géométriques telles que les positions, les distances, les aires, les volumes et les aires de surface peuvent également être calculées. Le système à base de connaissnces développé utilise une série de boucles « if...then » à l'aide du système PAVER (système de gestion de maintenance du revêtement des routes et des rues) ainsi que la littérature reliée. De nouveaux paramètres furent introduits au système dans le but de faciliter le processus de classification des détériorations incluant la forme des paramètres, l'orientation et certaines mesures géométriques. Un critère de priorité de gestion basé sur quatre paramètres fut développé. Ces paramètres incluent l'indice de condition du revêtement, la circulation moyenne journalière, l'emplacement des détériorations du revêtement et la classification des rues. Les mesures de surface ainsi que la prise de décision relative à la classification automatique furent validées et testées pour tous les types de détériorations. Le système développé démontra un grand potentiel de précision autant dans le mode de mesure que dans la phase de prise de décision. Ces résultats ouvrèrent une porte à la classification automatique potentielle des détériorations sans aucune intervention humaine.

Mots clés : système à base de connaissances, système de vision, mesures stéréos, détériorations de revêtements souples, priorités de gestion, systèmes de gestion de la maintenance du revêtement.
[Traduit par la rédaction]

Introduction

Road pavement represents a very large investment and, hence, pavement construction and rehabilitation are very important. Pavements can be evaluated by observing their deterioration in terms of the different types of distress they experience, such as cracking, distortion, and disintegration. It is essential to have a rapid and efficient data acquisition system as well as a pavement management system. Such systems would facilitate and reduce the costs of data collection, analysis, classification, and

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Written discussion of this article is welcomed and will be received by the Editor until August 31, 1998 (address inside front cover).

[1] A full report of the research reported in this paper can be found in Ghuzlan (1995).
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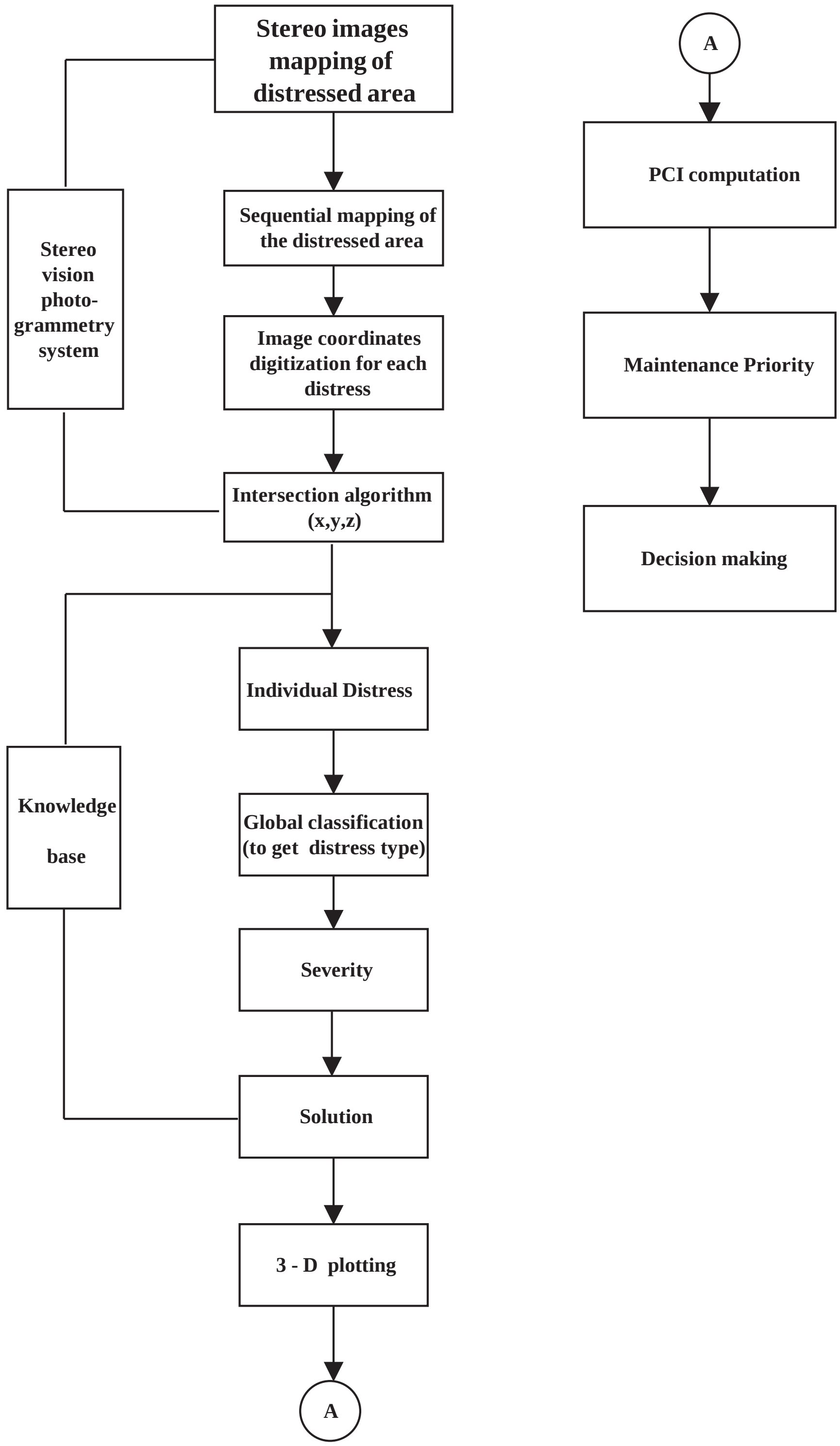
Fig. 1. Flow chart of research framework.



evaluation, as well as pavement maintenance management (Kaseko and Ritchie 1991). Reliability and accuracy are major advantages of such methods. Unfortunately, most data collection and distress classification and evaluation are done manually. The manual processes are unfavorable because of problems associated with time, cost, labor intensity, safety of the surveyors, and expert availability (Li et al. 1991).

Advancements in stereo digital machine vision technology and its integration with knowledge-based systems create an opportunity to overcome some of the problems associated with the manual methods (Corby et al. 1990; Sharaf and Abdul-Hai 1992; Kuo et al. 1992; Acosta et al. 1992). They can provide a low-cost, real-time geometrical imaging through digital photogrammetry without physically touching the object being

Table 1. Codes for selected distress types and severity levels.

Code	Distress type	Severity level
1011	Alligator cracking	Low
1012	Alligator cracking	Medium
1013	Alligator cracking	High
1021	Bleeding	Low
1022	Bleeding	Medium
1023	Bleeding	High
1031	Block cracking	Low
1032	Block cracking	Medium
1033	Block cracking	High
1041	Bumps and sags	Low

measured. Moreover, rule-based computer systems are user-friendly. Such systems can save time and money, as well as labor.

Once distresses are classified and their causes are known, the potential solutions and quantitative measurements of pavement conditions, such as pavement condition index (PCI), can be defined (Baker et al. 1987; Armitage 1991; Acosta et al. 1992). It is essential to set an efficient procedure for priorities of maintenance work based on the available budget, pavement conditions, and resources (Sharaf 1993). Due to budget shortage, maintenance priority setting should be chosen based on the optimal maintenance management system. Consequently, the distress locations with respect to the available maintenance equipment must also be considered.

This paper investigates the feasibility of incorporating a knowledge-based system with a close-range photogrammetric-based vision system for flexible pavement maintenance applications to automate much of the routine functions of distress classification. Applications of these classifications include inventory, classification, causes, repairs, and priorities for distresses maintenance activities.

Uses of photogrammetry in maintenance

The two most important distresses which define pavement performance are cracking and rutting. Conventionally, surveys that include geometry extent, severity levels, and type of these distresses are done manually by visual inspection. This direct measurement method is potentially dangerous, as the surveyors are exposed to traffic. A different approach for data collection that requires minimal field exposure is highly desirable.

Hintz et al. (1989) developed a combination of close-range photogrammetry data collection system and computerized analysis for evaluating pavement condition. This approach involves a non-metric camera (cameras of unknown interior geometry and requiring calibration) mounted on a van and supported by a microcomputer for analysis using a stereoplotter and software developed specifically for that purpose. The system uses stereo vision technology for distress data collection. Baker et al. (1987) developed a video image distress analysis system that uses a trailer towed by a truck, a video camera, a video recorder, and controlled lighting. A software package was developed for the system and can extract the crack type, crack length, and the total area of each of the cracks. Acosta et al. (1992) developed a system that allows the identification, classification, and quantification of commonly occurring pavement distress types in terms of severity and extent. The identification and classification of distresses is limited to distress types that can be quantified by width, length, geometry, or area covered by these distresses. An automatic pavement distress survey system was also developed by Fukuhara (1990) using a combination of a laser scanner, a photomultiplier tube, and a video camera connected to a signal processor. The use of specialized equipment may limit the application of the system for pavement distress analysis because of equipment cost and the added requirements of experts for its operation. Furthermore, Obaidat et al. (1997) used stereo vision technology to quantify the rut depth of flexible pavement.

From the previous literature review, it is clear that the trend in pavement evaluation is toward automated distress assessment. Consequently, automated pavement condition data collection and processing have become important study topics. The size, shape, and variations of each distress type, as well as the variation of the texture and color of the pavement surface, present a challenge to researchers (Li et al. 1991). Furthermore, the linkage between the automated distress data collection using stereo vision and the distress classification, severity level, and solution for repair has not yet been established.

Research method

Figure 1 shows a flow diagram for the general framework underlying this research. A hybrid system combining stereo vision and knowledge-based approaches is used in compliance with the objectives of this research. The following scheme, which depends on three-dimensional (3-D) outputs of stereo vision, is used for classifying distress types, severity levels, and options for repairs. The scheme is divided into four stages:

(1) arrange sequentially the distress 3-D data for the mapped sections, based on the following: distress boundary, data inside distress boundary, pavement edge, shoulder, and crack width;

(2) execute the knowledge-based system (called K-PAVER) on the data from step 1 to generate (*i*) distress type, (*ii*) severity level, (*iii*) options for repair, (*iv*) distress code, and (*v*) distress parameters;

(3) compute the pavement condition index (PCI) for the road sample units; and

(4) prioritize maintenance activities within the road network based on the average daily traffic (ADT), PCI, location of maintenance equipment with respect to the road network, and road classes.

Knowledge-based system K-PAVER

Function of K-PAVER

A knowledge-based system was developed to classify distresses and provide distress severity levels and repair options. The system uses three-dimensional coordinates (x, y, z) to define the surface of flexible pavements extracted from the vision system and some descriptive measures as inputs. The main objectives of incorporating the knowledge-based system with a stereo vision system are (*i*) to obtain reliable point locations for distresses without physically touching the pavement surface, thus resulting in time and labor saving; (*ii*) to minimize

Table 2. Decision matrix for distress types and severity levels based on shapes.

	Shape					
Parameter	Longitudinal	Rectangular	Circular	Sharp-angled	Half-moon	ELSE
ORC	✓	✓				
DFE	✓	✓				
AVD			✓			
ΔZ		✓	✓			✓
MDP			✓			
MRD		✓				
SDO		Lane	Shoulder	Drop-off		
LD			✓			✓
CW	✓	✓		✓	✓	

Table 3. Assisting parameters of knowledge-based system.

	Parameter											
Distress	SH	ORC	DFE	AVD	ΔZ	MDP	MRD	LD	SDO	CW	DIS	Subjective
Alligator cracking	✓									✓		✓
Bleeding												✓
Block cracking	✓											✓
Bumps and sags	✓	✓			✓						✓	
Corrugation	✓	✓			✓						✓	
Depression	✓				✓	✓						
Edge cracking	✓	✓	✓									✓
Joint reflection cracking	✓											✓
Lane/shoulder drop-off									✓			
Longitudinal and transverse	✓	✓	✓							✓		
Patching and utility	✓											✓
Polished aggregate												✓
Potholes	✓			✓	✓	✓						
Rail-road crossing												✓
Rutting	✓	✓	✓		✓		✓					
Shoving	✓	✓			✓							✓
Slippage crack	✓									✓		
Swell	✓							✓				
Weather and raveling												✓

hazards by improving the direct and visual pavement survey procedures; (*iii*) to provide a user-friendly system for nonexperienced users to apply the PAVER procedures, or any other pavement distress classification procedure, to classify distress types, severity levels, and options for repair, i.e., users need not have advanced knowledge in distress properties; (*iv*) to automate routine distress classification; and (*v*) to minimize the cost of data collection and decision making.

Data input

The data sets used as input in the knowledge-based system are basically outputs from the stereo vision system, i.e., the (x, y, z) surface measurements. A right-handed coordinate system is used and is defined as follows: the y-axis coordinates are positive in the direction of traffic movement; the x-axis coordinates represent the measurements crossing the road and are positive in the right direction transverse to traffic movement; and the z-axis coordinates are positive upward. Standard errors (precision measures), i.e., σ_x, σ_y, and σ_z, of the surface measurements form other input to facilitate volume, area, and surface area computations.

To simplify the classification procedures, surface measurements are divided into the following input sets:

(a) inner points of distress — 3-D points evenly distributed within the boundaries of a distress (excluding cracks);
(b) edge points of distress — 3-D points having approximately equal distances at the distress boundaries;
(c) pavement edge points — 3-D points on the edges of the pavement surface from the right side, i.e., the traffic movement direction;
(d) shoulder points — 3-D points on the edges of the right shoulder surface; and
(e) crack widths — 3-D points on the boundaries of cracks for computing crack widths.

Parameters used in the knowledge-based system

A number of parameters need to be computed in a knowledge-based system. Different criteria that are based on selected threshold values are used to define such parameters. The following is a list of the parameters developed, their symbols, and definitions:

(a) shape (SH), which defines the general geometric shape of

Table 4. Global classification for selected distresses.

Distress	SH (m)	OR (degree)	DFE (m)	AVD (m)	ΔZ (m)	LD (m)	SDO (m)	DIS (m)	Subjective characteristics
	Parameter*								
Alligator cracking	Sharp-angled								Surrounded by random cracks
Bleeding	Rectangular, circular, or ELSE								Bituminous film on the pavement surface
Blocking cracking	Rectangular								
Bumps and sags	Rectangular or ELSE				(+)			<3.0	
Corrugation	Rectangular or ELSE	Perpendicular			(+)			≥3.0	
Depression	Rectangular or circular	Not parallel			(–)				
Edge cracking	Longitudinal	Parallel	<0.60						
Joint reflection cracking	Longitudinal								Crack over a PCC slab joint
Lane/shoulder drop-off							>0.02		
Longitudinal and transverse	Longitudinal	Parallel or perpendicular	≥0.06						
Patching and utility cut patching	Rectangular, circular, or ELSE								Distressed pavement with color different from the surrounded pavements
Polished aggregate	Rectangular, circular, or ELSE								Smooth and bright color (looks white) aggregate at the pavement surface

*All parameters have the AND operator.

Table 5. Classification of severity level parameters for selected distresses.

Distress	AVD (m)	CW (m)	MRD (m)	MDP (m)	SDO (m)	Subjective characteristics	Severity level
	Parameter*						
Depression				MDP ≥ 0.051			High
				0.025 ≤ MDP < 0.051			Medium
				MDP < 0.025			Low
Rutting			MRD ≥ 0.025				High
			0.013 ≤ MRD < 0.025				Medium
			MRD < 0.013				Low
Edge cracking						No breakup or raveling around the edge crack	Low
						Some breakup or raveling around the edge crack	Medium
						Considerable breakup or raveling around the edge crack	High
	AVD ≥ 0.762			MDP ≥ 0.0254			High
	AVD ≥ 0.762			MDP < 0.0254			Medium
Potholes	0.457 ≤ AVD < 0.762			MDP ≥ 0.0254			High
	0.457 ≤ AVD < 0.762			0.0127 ≤ MDP < 0.0254			Medium

* All parameters have the AND operator.

a distress. Shapes could be longitudinal, rectangular, circular, sharp-angled, half-moon, or "ELSE" for any other shapes;

(b) orientation (ORC), which represents the layout of a distress in relation to the pavement edge. Consequently, distresses could be paralleli, perpendicular, or at an angle to the pavement edges;

(c) distance from edge (DFE), which represents the average distance between the centre of the plane coordinates of a distress and the right edge of the pavement with respect to the traffic direction, i.e., the minimum distance to either the right or the left side of the pavement edge;

(d) average diameter (AVD). This parameter is limited to cir-

Table 6. Classification of distress severity levels using the Acosta approach.

	Parameter*					
Distress	AVD (m)	CW (m)	MRD (m)	MDP (m)	Subjective characteristics	Severity level
Block or transverse cracking		CW < 0.0032				Low
		0.0032 ≤ CW < 0.0254				Medium
		CW ≥ 0.025				High
Rut			MRD < 0.0064			Low
			0.0064 ≤ MRD < 0.0254			Medium
			MRD ≥ 0.0254			High
Edge cracking		CW < 0.064			No breakup at the pavement edge	Low
		0.0032 < CW < 0.01			Some breakup at the pavement edge	Medium
		CW > 0.0254			Some spall at the pavement edge	High
Potholes	AVD ≥ 0.0152			MDP < 0.0254		Low
	AVD ≥ 0.0152			0.0254 ≤ MDP < 0.051		Medium
	AVD ≥ 0.0152			MDP ≥ 0.051		High

* All parameters have the AND operator.

cular distresses such as potholes, for which the average distress diameter can be computed;

(e) difference in elevation between the distress surface and the surrounding pavement surface (Δz). This parameter can be negative (in which case the distress surface is lower than the surrounding pavements, as in depressions) or positive (in which case the distressed area is higher than the surrounding pavements, as in swelling);

(f) maximum depth of distress (MDP). This parameter is needed for a number of distresses such as potholes or depressions, where Δz is negative;

(g) mean rut depth (MRD), which is the average rut depth of rectangular shapes;

(h) difference in elevation between the pavement edge and shoulder (SDO). This parameter is crucial for classification of the lane-to-shoulder drop-off distress;

(i) length of distress (LD), which is used in the case of longitudinal distresses, as in cracks. Other distress classifications, such as swell which requires the distress length, also require this parameter; and

(j) crack width (CW), which is limited to cracks. Two points with known (x, y, z) coordinates are used to compute the crack width.

Coding system

A coding system has been developed to facilitate the categorization process. The codes for distress type and severity level each has four digits to allow for expansion of the knowledge-based system. The coding system consists of the following:

(a) Codes for different distress types and severity levels: The first digit represents pavement type, 1 for flexible and 2 for rigid. The next two digits represent distress type. A sequential numbering is given for these two digits, starting from 0 and up to 99 different distress types and variations in distresses. The fourth digit represents the severity level of distress, 1 for low, 2 for medium, and 3 for high. Table 1 illustrates the codes used in this study.

(b) Codes for parameters: A lettering system is used to represent the parameters of the knowledge-based system.

Classification criteria

The distress classification process is divided into three main steps: (*i*) global distress classification, which categorizes distress types; (*ii*) severity level identification; and (*iii*) developing options for repair, which also prioritizes the repair options for each distress on the pavement. The classification decision then depends on a forward chain of if...then rules consisting of a stack of decision trees. Supplementary parameters, i.e., shape and geometric parameters, are used to assist the knowledge-based system in the classification process.

Global distress classification

In this stage, the distress type is decided using decision trees based on a stack of if...then rules and facts. The decision criteria used are as follows:

(a) Distress shape: A shape is selected from the six shapes listed in the previous section.

(b) Decision matrix: The matrix has been developed based on the needs of each distress type and severity level classification. First, the shape of distress has to be traced; then a decision is given on which parameters are to be computed from a matrix, i.e., not all parameters are computed. Table 2 shows the matrix used for this purpose.

(c) Global classification of distresses based on the parameters and shapes of distresses using a stack of if...then rules: Table 3 summarizes the parameters used for assisting the knowledge-based system for each distress type; Table 4 identifies the parameters used for classification of some distress types.

PAVER system severity level classification

In this stage, the distress severity level is determined using a stack of if...then rules and facts, based on the PAVER system (Shahin and Walther 1990). The input for this stage is the

Table 7. Options for repair of selected distresses.

Distress type	Severity level	Options for repair
Alligator cracking	Low	Do nothing
		Surface seal
		Overlay
	Medium or high	Partial or full depth patch
		Overlay
		Reconstruct
Bleeding	Low	Seal cracks over 1/8 inch
		Surface seal
	Medium or high	Apply sand/aggregate and roll
Block cracking	Low	Seal cracks over 1/8 inch
		Surface seal
	Medium or high	Seal cracks
		Recycle surface
		Heater scarify and overlay
Bumps and sags	Low	Do nothing
	Medium or high	Cold mill
		Shallow, partial full depth patch
Corrugation	Low	Do nothing
	Medium or high	Reconstruct
Depression	Low	Do nothing
	Medium or high	Shallow, partial full depth patch
Edge cracking	Low	Do nothing
		Seal cracks over 3.0 mm
	Medium	Partial depth patch
		Seal cracks
	High	Partial depth patch
Joint reflection cracking	Low	Seal cracks over 3.0 mm
	Medium	Seal cracks
		Partial depth patch
	High	Partial depth patch
		Reconstruct joint
Longitudinal and transverse cracking	Low	Do nothing
		Seal cracks over 3.0 mm
	Medium	Seal cracks
	High	Seal cracks
		Partial depth patch

output from the global distress classification, i.e., the distress type. Table 5 summarizes the rules used in severity level classification for some types of distresses.

Acosta approach for severity level classification

Another deterministic approach is also used to classify distress severity (Acosta et al. 1992) for comparison with the PAVER approach. At this stage, severity levels of some distresses (including block or transverse cracking, rut, edge cracking, and potholes) are known. The input for this stage is the output from the global classification stage. In the case of cracks, this method is mainly based on crack widths. Thus it is a simple method and has only one parameter to be considered. Table 6 identifies the parameters used for classification of severity levels for each distress type. These parameters are stacked in a set of if...then rules for the development of the knowledge-based system.

Options for repair classification

After deciding on the type of distress and its severity, a maintenance measure need to be identified and repair options need to be prioritized. A set of if...then rules is also developed for the knowledge-based system, based on the PAVER system. The rules and facts are listed in the order of priority to simplify the decision-making process. Table 7 shows the repair options for some types of distresses based on the PAVER system.

Software development

A computer software is needed to capture images, digitize stereo image points, calibrate the camera system, define the surface, determine distress shapes and distress parameters, classify distresses, determine distress severity levels, identify repairs, and suggest maintenance priorities. Such software is developed or modified within the knowledge-based system. Commercial software are available for image capture and digitization only. Hence, a software package which performs the following tasks was developed: (*i*) camera calibration; (*ii*) 3-D intersection positioning; (*iii*) auxiliary measurements such as areas, surface areas, volumes, perimeters, and lengths; (*iv*) defining shapes and other parameters of distress; (*v*) knowledge-based global distress classification; (*vi*) knowledge-based distress severity level classification using the PAVER and Acosta approaches; (*vii*) knowledge-based solutions for repairs; and (*viii*) priority index for maintenance repairs.

The software package is called K-PAVER, i.e., a knowledge base using the PAVER system. The programs are written in FORTRAN and are intended for a PC user-friendly environment. Human intervention is minimal in order to facilitate the application of artificial intelligence in the computational algorithms.

Stereo vision system equipment

The hardware configuration utilizes an off-the-shelf PC-based vision system, which is part of the facility at the Surveying and Photogrammetry Laboratory, Department of Civil Engineering, Jordan University of Science and Technology. The system consists of the following hardware components:

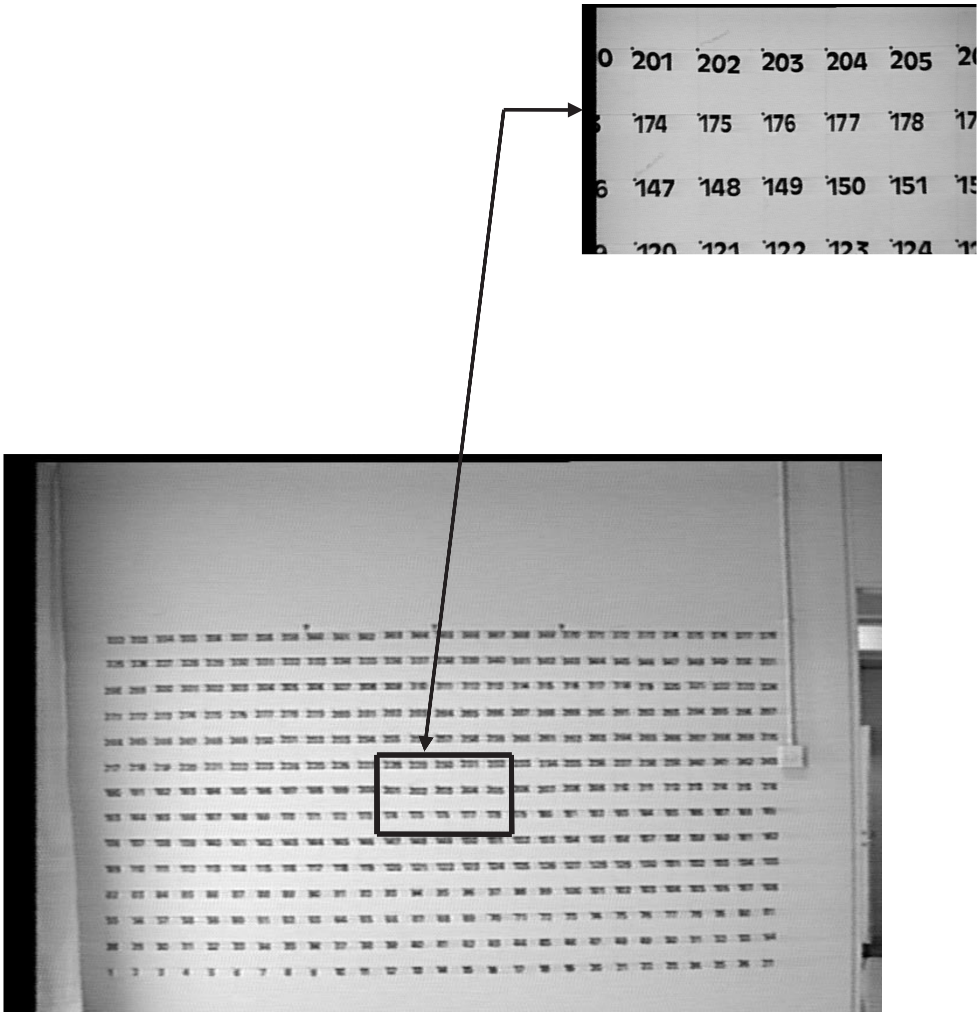
(a) A DTK 486 PC equipped with a SVGA monitor and an EPIX frame grabber with 20 MHz pixel close and 1 MB of image memory. The DTK 66-MHz 486/AT PC is equipped with 8 MB random access memory, 550 MB hard disk drive, and 5.25 and 3.5 inch high-density drives. Images are captured using standard PAL resolution, i.e., 752×480 pixels using 256 gray levels.

(b) Two 50800 8-mm Samsong CCD camcorders equipped with a zoom lens capability. For the purpose of this study, video images are acquired with the zoom lenses located at a fixed focal setting of 11 mm. The cameras are mounted on a stand.

(c) The system is supported with video monitors, dot matrix printers, and scanners.

The hardware configuration includes simple and inexpen-

Fig. 2. Planar wall calibration field.



sive components, which have become common household items, except the frame grabber. The primary function of this vision system is limited to image capture and analog-to-digital conversion of signals. An interactive program called SVIP is used to digitize the video images into 256 gray levels (8 bits per pixel) with a resolution of 752(H) × 480(V) pixels. The digitized images are stored as DOS files in two formats, either (x, y) or TIF format.

Calibration field

A planar wall containing over 300 black dots on a white background was built specifically for the purpose of implementation of this research program. The dots are 5 mm in diameter and are evenly distributed 10 cm apart. The dots are numbered, also in black. Consequently, distances and points in three-dimensional space could easily be defined using this calibration field. Figure 2 shows an image of the calibration field.

The use of planar walls for calibration purposes has the capability to enforce the two bundle of rays, i.e., the conjugate rays of stereo images acquired by a camera, to intersect at a plane. Thus, it provides the geometric distortion parameters not only on the columns but also on the rows of the images (Obaidat 1994). The calibration field could also be any planar wall, such as a brick wall, available near the pavement distress area.

Experimental study

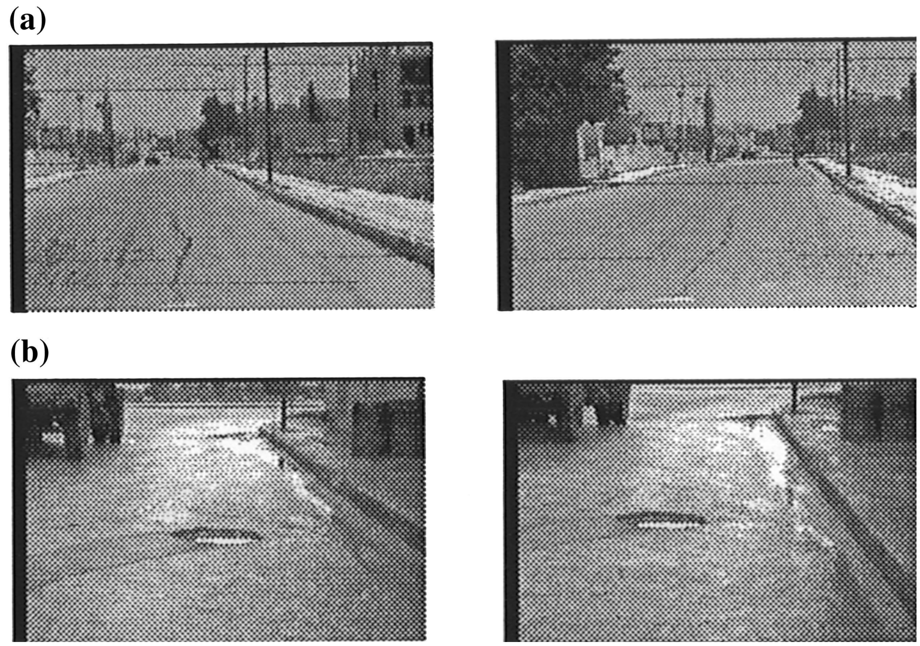
Classification of distress and its severity is a major step in the determination of pavement condition index (PCI), which is a measure of pavement condition in order to perform maintenance action. To obtain accurate PCIs, a reliable measurement method in the classification process is needed. Stereo vision application for data collection is needed to automate the measurements of distress geometry and its classification. This automation process not only results in time saving but also enhances safety of inspection.

In this section, actual field examples are presented. The data collection is automated using a PC-based vision system. Figure 3 shows two pairs of stereo images captured for longitudinal crack and pothole distresses using a dual camera setup (i.e., each distress area should have two images, one from the left camera and the other from the right camera).

Data acquisition procedures

The following procedures are used for obtaining geometric surface distress measurements:

Fig. 3. Stereo images of (*a*) longitudinal and (*b*) pothole distresses.



(a) capturing of calibration images using dual cameras;
(b) capturing of images for distress areas;
(c) re-capturing of calibration images after capturing of field images;
(d) using SVIP program to digitize images in (*X*, *Y*) binary format;
(e) finding stereo conjugate image coordinates for both calibration and distress images;
(f) finding the calibration parameters;
(g) quantifying 3-D distress coordinates;
(h) representing graphically the distress areas (2-D and 3-D); and
(i) comparing with the actual distress data measurements.

Longitudinal crack

Stereo images are filmed for longitudinal cracks in Irbid, Jordan. These images are processed to obtain the 3-D coordinates of selected points on the pavement surface. The points are first taken along the crack itself and are called outer points of distress. The code (–1 1 1 1 1 1) is entered at the end of this 3-D data set as an indicator for the K-PAVER knowledge-based system that processing of the outer points is complete. Next, the inner points are processed. Because cracks do not have inner points, the code (–2 2 2 2 2 2) is entered; this code signals the beginning of the right edge pavement points. At the end of the right edge pavement points, another code, (–3 3 3 3 3 3), is used to indicate the beginning of right shoulder points. These are followed by the code (–4 4 4 4 4 4) and the coordinates of two points, one on each side of the crack, to be used for crack width computation. The code (–5 5 5 5 5 5) indicates end of a data set, and (–6 6 6 6 6 6) indicates beginning of a new data set for another distress. This arrangement gives flexibility in analyzing and making decisions on distress type and severity when more than one distress is involved, using one data file.

The K-PAVER output file contains options which have different computed parameters for areas and volumes. Another output menu contains several parameters that are used to make decisions on the distresses. If any of these parameters are not applicable to the distress type, the code N/A will appear. A third output menu contains the distress type, severity level, options for repair, and the distress code. The threshold values used in decision making can be changed by the user.

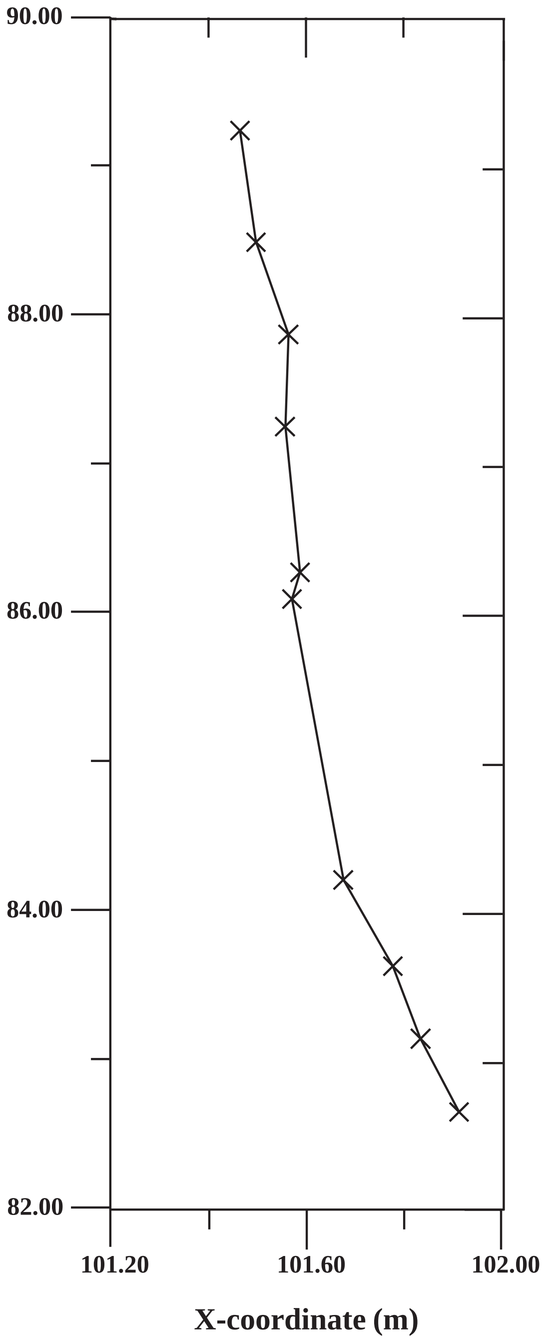
Figure 4 shows a 2-D plot for the distressed area extracted from stereo vision for the longitudinal crack. The accuracy of surface measurement of coordinates of the selected points depends on the accuracy of image matching, the camera calibration process, and the camera configuration (Faig et al. 1990).

Actual measurements of the distresses studied are taken on tape. This alternative procedure is done to compare the PC-based vision system data with the actual measurements. Specific measurements are needed for each distress, depending on the knowledge-based parameters. For example, in the case of cracks the following parameters are computed: distance of crack from pavement edge, the orientation of the crack with respect to the pavement edge, crack length, and crack width. In the case of depression distress, the depth and shape of the distress are required. Table 8 shows the actual measurements, measurements extracted from stereo vision, and the difference between the two techniques for longitudinal cracks. Table 9 reports the output parameters of K-PAVER for this distress. Slight decision and measurements differences are found between the stereo vision and manual techniques. The final decision by the K-PAVER knowledge-based system agrees with that obtained from actual measurements and visual survey. K-PAVER gives the right decision of distress using an automated approach without human intervention. This is a sign of a new era of application of artificial intelligence techniques to pavement maintenance.

Pothole classification

Three-dimensional coordinates are extracted for a pothole dis-

Fig. 4. Two-dimensional plot of the longitudinal crack.



tress by manual and stereo vision measurements. The selected points are located at the pothole boundary, inside the pothole, and at the pavement edge. Table 10 shows the output from the knowledge-based system (K-PAVER). As illustrated, the difference between the manual and knowledge-based system results is negligible.

Maintenance priority

A logical maintenance priority approach has been developed. The approach takes into consideration four parameters: pavement condition index, PCI; average daily traffic, ADT; distance from the street of equipment to be maintained, *R*; and road class, *C* (arterial, collector, or local roads). The importance of each parameter is weighted based on the maintenance administrator's decision; i.e., a separate weight is given for each parameter. A priority index (PI) for maintenance of urban road network is introduced. The larger the value of the index the greater is the necessity for repair. The advantage of this approach is that once the maintenance priorities of the streets are known, the budget could be distributed based on the priority index or any other selected criteria. The priority index could be computed using two approaches: the formula approach and the ranking approach.

Table 8. Measurements of longitudinal cracks.

Parameter	Manual	Stereo vision	Difference
Crack length (m)	7.1	6.62	0.48
Distance from right edge (m)	1.95	1.77	0.18
Crack width (m)	0.03	0.10	0.07
Condition	Nonfilled	Nonfilled	No difference

Table 9. K-PAVER parameters and decision for longitudinal cracks.

Crack width (m)	0.101
Crack length (m)	6.620
Distance from right edge (m)	1.770
Orientation of crack (degree)	46.220
Distress type	Longitudinal and transverse cracking
Severity level	High
Code	1103
Options for repair	Seal cracks; partial depth patch

Table 10. K-PAVER decision for potholes (circular).

Area (m^2)	0.248
Volume (m^3)	0.013
Perimeter (m)	2.074
Distance from edge (m)	na
Orientation with respect to the pavement edge	na
Average diameter (m)	0.602
Maximum depth of distress (m)	0.08
Mean lower in elevation (m)	na
Distress length (m)	0.63 m
Distance between successive distresses (m)	na
Distress type	Pothole
Severity level	High
Code	1133
Options for repair	Full depth patch

Formula approach

A simple maintenance priority formula in terms of the four parameters (PCI, ADT, *R*, and *C*) is derived. These parameters (variables) are normalized by dividing each by its average value in the road network. The normalization process is a type of weighting procedure. The priority index calculated from the derived formula takes into account the effect of each variable. A variable appears in the numerator if PI is proportional to that

Table 11. Priority index using the formula and ranking approaches.

Formula approach							Ranking approach					
Street rank	ADT (vph)	PCI	R (km)	Class	Street name	PI (%)	Street name	W_1	W_2	W_3	W_4	PI (%)
1	3800	8.0	1.88	1	13	28.10	4	0.301	0.027	0.023	0.5464	9.68
2	5581	24.0	1.69	1	4	15.31	6	0.020	0.100	0.151	0.5464	8.81
3	4600	17.6	2.34	1	12	12.42	11	0.151	0.036	0.050	0.5464	8.42
4	5038	28.1	1.89	1	5	10.55	2	0.151	0.043	0.100	0.5464	7.84
5	5178	30.2	2.06	1	11	9.26	5	0.100	0.030	0.037	0.5461	7.70
6	4872	30.8	1.95	1	15	9.02	15	0.075	0.038	0.043	0.5464	7.57
7	3330	49.0	1.78	1	3	4.25	3	0.043	0.075	0.027	0.5464	7.46
8	2750	33.0	2.57	1	2	3.61	12	0.060	0.022	0.060	0.5464	7.41
9	1712	20.5	1.44	2	8	3.23	13	0.050	0.020	0.033	0.5464	7.01
10	1709	41.0	1.70	2	7	1.36	1	0.021	0.301	0.030	0.182	5.76
11	1693	46.8	1.63	2	9	1.23	10	0.025	0.025	0.301	0.182	5.75
12	1390	23.2	3.65	3	10	0.61	14	0.023	0.151	0.075	0.182	4.65
13	1000	72.6	2.65	1	6	0.58	7	0.030	0.060	0.025	0.273	4.18
14	1200	78.3	2.37	3	14	0.24	9	0.027	0.050	0.021	0.273	4.01
15	1000	90.0	1.80	3	1	0.23	8	0.075	0.038	0.020	0.273	3.77

variable. Conversely, if an inverse relation holds, the variable appears in the denominator of the derived formula. Equal weights are assigned to all variables, since different weights will not affect the ranking result. However, the variables could be weighted upon request. The following equation for priority index is adopted for road network maintenance:

$$[1] \quad \mathrm{PI} = (\mathrm{ADT}/\mathrm{ADT}_{\mathrm{avg}}) \,/\, [(\mathrm{PCI}/\mathrm{PCI}_{\mathrm{avg}}) \times (R/R_{\mathrm{avg}}) \times (C/C_{\mathrm{avg}})]$$

where the subscript avg denotes the average value of the variable.

The values of PI obtained for the road network are arranged in descending order, together with the corresponding street numbers. Thus, the priority rank for every street is known.

Ranking approach

The ranking approach is another type of weighting criterion of the streets data for each variable. For each variable, the streets data are sorted in descending order. Consequently, four ordered arrays of ADT, PCI, R, and C are constructed. These arrays contain only the rank (identification) of the street which is an indication of the value of the variable. The smaller the rank value of the street the higher is the value of the variable for that street. Except for the road class, which has assigned ranking numbers of 1 for arterial, 2 for collector, and 3 for local, it is noted that ADT values are arranged in descending order, whereas PCI, R, and C are arranged in ascending order because PI varies inversely with these variables.

It is obvious from the previous discussion that the weighting procedures should be inverted, i.e., the lower the rank the higher the PI of that street. The weight of the rank for every street of every variable therefore can be computed from the following formula:

$$[2] \quad W_{ij} = [(1/R_{ij}) \,/\, (\Sigma\, (1/R_{ij})] \times 100\%$$

where W_{ij} is the weight for street i of variable j and R_{ij} is the rank for street i of variable j.

This means that each street will have four W_{ij}. The priority index for street i, PI_i, is therefore given by

$$[3] \quad \mathrm{PI}_i = W_{i1} + W_{i2} + W_{i3} + W_{i4}$$

where W_{i1}, W_{i2}, W_{i3}, and W_{i4} are the weights for street i of the variables ADT, PCI, R, and C, respectively.

Table 11 shows the procedures to compute the priority index of each street based on the actual data of selected streets in Irbid city using the formula and ranking approaches. The two methods give slightly different results for street ranking, for the purpose of maintenance priorities.

Conclusions

This research was aimed at developing a stereometric knowledge-based system for pavement distress classification. The following are the most signification findings of this work:

1. An automated knowledge-based system for distress classifications was developed which shows a great potential in pavement evaluation, distress classification, severity levels, and suggestions for repairs. This development is a step toward real-time distress classification.

2. Data acquisition for pavement distresses using automatic stereo vision proves to be less time-consuming and less costly, compared with manual data collection. A greater saving in time can be obtained through the use of digital data reduction procedures.

3. A hybrid stereo vision and knowledge-based system for distress classification, with minor human intervention, could be used effectively in place of manual procedures and fully automated artificial intelligence systems.

4. The PAVER and Acosta systems for distress classification provides useful knowledge that could be used in the decision trees within the knowledge-based system.

5. Camera configuration and image resolution affect the accuracy of the extracted geometrical surface measurements of distresses. However, differences between the actual and stereometric measurements are found to be insignificant.

6. A maintenance priority criterion has been developed, based on the parameters ADT, PCI, distance of distresses from equipment, and street class.

7. Simulation data and actual examples for the integration of stereo vision system and knowledge-based system have

been demonstrated to validate the use of the developed system and show a great potential in distress classification.

The results of this research led to the conclusion that a stereometric knowledge-based system could be effectively used for classifying distress types, severity levels, and options for repair. This potential can most fully be exploited if further research is directed toward the following tasks: (*i*) automate the stereo matching process; (*ii*) define a deterministic approach using image processing technique to overcome the descriptive limitations of some distresses of the developed knowledge-based system; (*iii*) study the effect of camera configuration, image resolution, and image scale on geometric surface measurements of distresses; (*iv*) investigate the effect of the use of 3-D field camera calibration on the accuracy of the extracted geometrical distresses characteristics; (*v*) develop an automated procedure to compute pavement condition index; (*vi*) investigate the effectiveness of distress classification using artificial neural network; and (*vii*) provide a flexible image capturing procedure which prevents hazard during the field work process.

The technique described in this paper can be beneficial to any road authority because of its potential for integrating additional computer analyses into the maintenance engineering field. Furthermore, it can be extended to include applications in geographic information systems to identify and correlate pavement distress type and severity level with traffic volumes, pavement designs, pavement ages, and other common factors.

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