Methods and Algorithms for Automated Analysis of Pavement Images

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The collection and analysis of pavement distress data are a primary component of any pavement management system. Different approaches for automatic interpretation of asphalt pavement distresses, recorded on video or photographic film, with emphasis on segmentation and classification of digitized distress pavement images are examined. Segmentation deals with the problem of extracting the objects of interest from the background, whereas classification assigns distresses to corresponding distress types. Results from the application of the different methods on a data set of asphalt pavement images are presented. Alternative segmentation and classification approaches and the effectiveness of global geometrical descriptors characterizing the various distress classes are evaluated. Issues associated with the accuracy and validity of the proposed methods are discussed and possible sources of error examined. Directions for further research are also identified.

The collection and analysis of pavement distress data are a primary component of any pavement management system (*1*,*2*). Currently pavements are usually manually inspected for collection of surface distress data. This form of inspection suffers from several drawbacks:

1. It is slow, labor intensive, and expensive and therefore only a small fraction of the pavement section to be assessed can be inspected. This low sampling rate clearly reduces the accuracy of the process.
2. It is subjective and hence consistency between surveys made by different inspectors on the same section may be low.
3. Repeatability may also be poor, i.e., the assessment of a section by a given inspector may differ between two inspections even when they are spaced so that little extra deterioration has occurred.

The implications of these drawbacks are obvious, at least in a qualitative sense. Inaccurate condition assessment may result in overmaintaining of pavements, or in expensive deferral of urgently needed repair.

In order to eliminate the drawbacks of manual inspection, automation of the process is currently receiving increased attention because of its potential to provide highway agencies accurate and detailed data on pavement condition. Among the various technologies, the one based on image collection is the most popular. Various systems exist, or are under development, that record the surface of the pavement on video tape or photographic film and subsequently analyze them either manually at a laboratory, or automatically using image processing and pattern recognition methods (*3*–*5*). The majority of the systems in the latter category operate off-line. The data are recorded by the moving vehicle and the film or tape is brought to the laboratory for processing, for example, overnight.

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Figure 1 shows the main components of an automated inspection system that is based on imaging technology. The first two components of the system are hardware and the last two are software related. The focus is on software aspects of automated pavement inspection systems. Experience with certain preprocessing operations and approaches for classification of pavement images into the various distress classes of interest are described. The system under development is currently not appropriate for real time operations and requires the calibration of various parameters using a set of sample images from the data set to be analyzed. The discussion is restricted to flexible asphalt pavements, which constitute the majority of U.S. highways. Finally, conclusions on the various aspects of the problem and recommendations for further research are provided.

PREPROCESSING

Preprocessing of digitized images involves operations such as enhancement of the images and segmentation. The focus of the discussion is on segmentation, the process of extracting objects of interest (distresses) in an image from the background and obtaining a binary image (where the distresses are indicated by black pixels and the background by white).

Segmentation is an important step in the entire process and various general methods exist for segmenting images (*6*). The effectiveness of segmentation greatly depends on the quality of the acquired images, which is affected by the hardware configuration used for image acquisition. For example, some data collection systems use artificial lighting for data acquisition. Although use of artificial light is an improvement over natural light, it may still require special preprocessing algorithms to eliminate the effects of nonuniformity of illumination. In addition, there are several intrinsic properties of flexible pavement images that make segmentation difficult:

1. The contrast between distresses and background (undistressed pavement) is frequently low, because the distribution of intensity of distressed pixels exhibits considerable overlap with the distribution of the background. This is because of the texture of asphalt pavements mainly determined by the presence of aggregates of variable color and brightness.
2. The area of a distress is small compared with the area of the background (the number of pixels in the digitized image representing distresses is small).

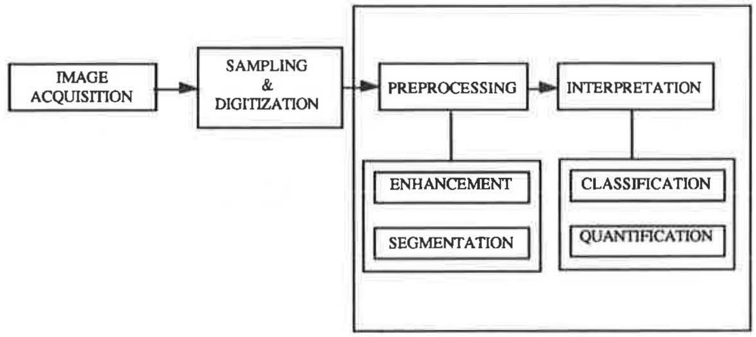


FIGURE 1 Components of automated pavement inspection systems.

Koutsopoulos et al. (*7,8*) examined in detail various approaches for segmentation of pavement images and found that a version of the relaxation method suggested by Bhanu and Faugeras (*9*) and Rosenfeld and Smith (*10*) yielded promising results. They also developed a simple thresholding method for segmentation. The threshold is determined using regression analysis with the mean and the variance of the distribution of gray levels as explanatory variables. This method also yielded promising results. These two methods (relaxation and regression thresholding) are further evaluated using the accuracy of subsequent classification as criterion.

INTERPRETATION

The interpretation component of automated pavement inspection systems includes two tasks: (a) classification of objects into one of the classes of interest (such as undistressed pavement, longitudinal distress, transverse cracking, alligator cracking, and block cracking), and (b) quantification, i.e., measurement of the extent and severity of the corresponding distress. The discussion focuses on classification, although the methods that are described could also be extended to cover the quantification task.

Among the various approaches to classification, statistical methods are popular (*11,12*). A common component of statistical methods is the representation of the object to be classified by a feature vector. The choice of the descriptors included in the feature vector is based on their discriminatory power, i.e., their ability to differentiate among the various classes. If n measurements are made on each object, the resulting feature vector will be a point in an n-dimensional feature space. The basic problem is to partition this feature space so that there is one region for each class. Objects to be classified are assigned to the class in whose region their feature vector lies.

If the probability distributions of the feature vector can be estimated (from a sample that is available), statistical methods such as Bayesian analysis may be used for the classification. In this case, it is common to assume that the feature vector has a multivariate Gaussian distribution, and hence the problem is reduced to one of estimating the corresponding parameters using standard statistical techniques.

An approach that does not require the distribution of individual descriptors in the feature vector is based on the logit model (*13*). The various classes constitute the alternatives and the systematic utility of each class is defined using the descriptors in the feature set as alternative specific variables. The probability that an object with feature vector $\mathbf{x}$ belongs to Class i is given by

$$\text{Prob}(i) = \frac{e^{V_i}}{\sum_m e^{V_m}}$$

where V_m is the systematic utility of Class i, defined as

$$V_i = \sum_{j=1}^{n} a_{ij} x_j$$

When no assumptions are made on the underlying distributions of the feature vector, the minimum distance classifier is a popular classification method. This approach is most effective when the class characteristic variables have clustering properties, i.e., when points corresponding to the feature vector of a given class tend to form clusters in n-dimensional space. In the single prototype version of this approach, each Class i is represented by a single prototype, assumed to be representative of that class, with Feature Vector $\mathbf{z}_i$. An object with Feature Vector $\mathbf{x}$ is assigned to the ith class if $D_i < D_j$ for all $j \neq i$, where the distance D_i is given by

$$D_i = \|\mathbf{x} - \mathbf{z}_i\| = (\mathbf{x} - \mathbf{z}_i)^T(\mathbf{x} - \mathbf{z}_i)$$

If the data are more irregularly clustered, another classification scheme can be devised by using more than one prototype $(s_1, s_2, \ldots, s_N)$ for each class. Then the object to be classified is assigned to the class of the prototype that minimizes the defined distance.

In one of the few documented studies in classification of pavement images Maser (*14*) uses a six-dimensional feature vector to represent each object. The features computed are the fraction of the image occupied by the distress, the ratio of minimum to maximum moment of inertia, the inclination of the axis of minimum inertia to a fixed axis, the ratio of the area of the distress to the area of the rectangular bounding box enclosing it, the ratio of the width over the length of the bounding box, and an average width obtained by dividing the area of the object by the length of the bounding box. A minimum distance classifier was used to assign the object to one of six classes, namely longitudinal cracking, transverse cracking, alligator cracking, patching, bleeding, and uninteresting blobs. The prototype vector for each class was defined using some typical examples for each class. Because of the small and rather ideal data set used for this experiment, it is difficult to draw any conclusions on the potential of this approach. However, the feature vector used for the analysis captures basic characteristics of the images under examination and will be used in the investigation.

THE CLASSIFICATION STRATEGY

In addition to the usual approach, which consists of simultaneous examination of all possible classes and assignment of the object under consideration to one of these classes, a hierarchical approach is investigated for classification of pavement distresses. This classification strategy is based on the decision tree shown in Figure 2 and according to Dattareya and Kanal (*15*) provides a more general and flexible classification framework.

The top node of the tree differentiates between images with distresses and images without any distress. From the object node downwards, object classification is of concern. Once a distress has been identified, at each subsequent node a decision is made that assigns the object to a subgroup of distresses. The object node branches into one-dimensional (1–D) and two-dimensional (2–D) distresses. The 1–D distresses consist of linear cracking, i.e., longitudinal and transverse cracking. The 2–D distresses are divided into cracking and noncracking objects. The 2–D cracking distresses are further divided into alligator and block cracking. The noncracking 2–D distresses are divided into patches and potholes.

It is expected that segmented distress-free images consist of small objects that can be eliminated easily by a noise-cleaning process. Distress-free images, therefore, can be identified using total area as a classification criterion (*8*). The distinction between 1–D and 2–D distresses is based on the fact that linear cracks are more elongated than the remaining distresses. 2–D cracking distresses (alligator and block cracking) and noncracking distresses differ in that the latter distresses are fuller or denser. Alligator and block cracking are distresses that have different structural causes, and hence a distinction between them needs to be made for maintenance reasons; unfortunately the shape differences between the two

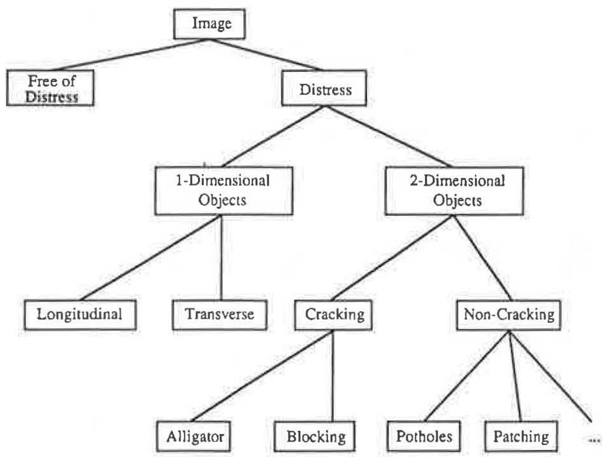


FIGURE 2 Distress classification hierarchy.

distresses are less obvious. In general, block cracking consists of approximately rectangular crack patterns, although alligator cracking consists of more irregular, small polygons (*16*). The distinction between patches and potholes may be based on their density and the geometrical regularity of their shape.

This classification strategy provides several advantages because it allows the use of different classification methods and feature vectors at different levels of the hierarchy, depending on the complexity of the corresponding classification task. Therefore it may result in reduction of the computational effort required for overall classification.

CASE STUDY

The data set used for this analysis consists of 28 images, provided by PCES (*17*), which belong to four distress classes: longitudinal cracking (2 images), transverse cracking (8 images), alligator cracking (11 images), and block cracking (7 images). The images are digitized and stored as matrices of dimension 512 × 512. Each entry of the matrix represents the gray scale level of the corresponding pixel (with values between 0 and 255). This data set was used to compare the two segmentation approaches presented earlier, evaluate the effectiveness of various descriptors in the feature vector, and assess the overall classification approach. Unfortunately, because neither potholes nor patches are included in the data set it was not possible to draw any conclusions concerning these distresses.

Segmentation Results

The regression equation that was estimated for the determination of the optimal threshold corresponding to the data set described is as follows:

$$T^* = 18.60 + 0.79\mu - 0.046\sigma^2$$

where μ is the mean and σ^2 the variance of the histogram of intensity of the image. The R^2 value of the regression was 0.80 and the parameters are in general statistically significant; the t values for the coefficients are 0.60, 7.17, and 2.66; furthermore the tests performed demonstrate that the values of the parameters are only slightly affected by the sample size.

In Figure 3, the binary (segmented) images obtained by the relaxation and the regression threshold for two different distress types are compared. The two methods perform similarly; however, the most important criterion for the selection of a segmentation method is how the segmented images affect the accuracy of the classification process that follows.

Classification Results

The performance of classification procedures is usually evaluated on the basis of error rates (misclassification probabilities), and various methods exist for the estimation of error rates (*17*). A common and popular method is the use of the available sample as both the training and the test set. Using this method, error rates are easy to estimate; however, these

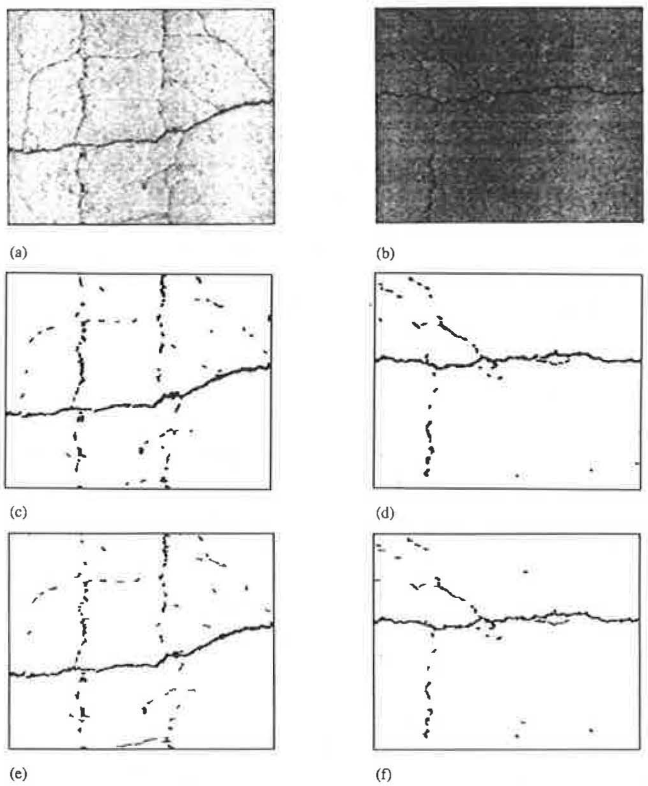


FIGURE 3 Examples of segmentation of pavement images: (a) alligator cracking, (b) block cracking, (c) segmentation by relaxation, (d) segmentation by relaxation, (e) segmentation by regression, and (f) segmentation by regression.

estimates are optimistic (they underestimate the true error rates). Better estimates may be obtained by splitting the sample into two sets, the training and test set. The training set is used for the calibration of the classification function and the test set for evaluation. This method, although it overcomes the bias problem, suffers from two major drawbacks that limit its use: (a) it requires large samples, and (b) the classification function that is estimated and subsequently evaluated does not use all the available information. A third approach which is computationally more involved, but provides almost unbiased estimates of the error and does not require large samples, is Lachenbruch's holdout procedure. In the following analysis, the first method was used (the conclusions subsequently drawn are not affected by the potential bias in the estimation of the error rates).

The feature vector used for the classification of the images into the four classes mentioned earlier consists of the following geometrical measures:

1. Density. The area of object divided by the area of the bounding box; the bounding box is defined as the smallest rectangle with sides parallel to the image coordinate axes that fully encloses the object; area is the number of pixels that constitute the object under consideration. The density of an object is expected to have lower values for 2–D cracking and higher values for contiguous 2–D distresses such as potholes.
2. Angle. The angle of inclination of the object's axis of minimum inertia (or axis of elongation) to the horizontal. The angle of inclination is useful for differentiating between longitudinal and transverse cracking.
3. Inertia Ratio. The ratio of the principal moments of inertia, i.e., the ratio of the minimum to the maximum moment of inertia, with the origin located at the center of gravity of the object. The inertia ratio is used as a measure of the elongation of an object. It is expected to have lower values for linear cracking and higher values for 2–D objects.
4. Aspect Ratio. The ratio of the lengths of the two sides of the bounding box. It is a more direct measure of the elongation of an object than the inertia ratio. However, because the aspect ratio is directly related to the bounding box, the measure is sensitive to existence of noise in the object.

Simultaneous Classification

For each distress class, the mean value for the descriptors in the feature vector over all members of the class in the data set was estimated. A single prototype was determined for each class using the mean values as the representative feature vector. Table 1 presents these values for each class for both the relaxation and regression segmented images.

Table 2 presents the classification of the images to the various classes according to the minimum distance classifier (for both the relaxation and the regression segmented images). In both cases, the same overall classification accuracy of 75 percent is obtained. Clearly most of the misclassifications occur between alligator and block cracking.

From the set of the various descriptors considered, the feature vector consisting of angle, aspect ratio, and density was the most successful in classifying the distresses. The inertia ratio did not perform particularly well. Inclusion of this descriptor in place of the aspect ratio caused even more misclassifications; more alligator images were classified as block cracking, whereas block cracking images were misclassified as alligator and longitudinal cracking.

TABLE 1 FEATURE VECTOR FOR RELAXATION-REGRESSION SEGMENTED IMAGES

DISTRESS TYPE	INERTIA RATIO		DENSITY		ASPECT RATIO		ANGLE°	
	Relax.	Regr.	Relax.	Regr.	Relax.	Regr.	Relax.	Regr.
Alligator	0.378	0.388	0.0272	0.0212	0.87	0.87	56.7	51.7
Block	0.151	0.202	0.0262	0.0216	0.76	0.76	28.6	29.2
Transverse	0.014	0.014	0.0698	0.0476	0.21	0.21	7.4	2.4
Longitudinal	0.050	0.043	0.1463	0.075	0.25	0.25	85.4	85.1

TABLE 2 SIMULTANEOUS CLASSIFICATION RESULTS, RELAXATION AND REGRESSION (PERCENT CORRECTLY CLASSIFIED IN PARENTHESES)

Distress Type	Total Number	Classified as			
		Alligator	Block	Longitudinal	Transverse
Alligator	11	8 (73%)	3	0	0
Block	7	2	4 (57%)	0	1
Longitudinal	2	0	0	2 (100%)	0
Transverse	8	0	0	0	8 (100%)

Table 3 presents the results of the estimation of the logit model with alligator cracking used as the base alternative. The parameters are in general statistically significant. Tables 4 and 5 present the classification of the various distresses as suggested by the logit model. The overall classification accuracy (a measure not usually recommended for evaluating model performance) is 78 and 82 percent for relaxation- and regression-based segmentation, respectively. An important difference from the results obtained using the minimum distance classifier is the types of misclassification that occur. Images with alligator cracking are classified with very high accuracy; however, only 28 percent of block cracking is correctly classified, with the majority of the images (57 percent) classified as alligator cracking. Another difference between the two approaches is that the use of inertia ratio performed as well as the aspect ratio when used in the logit model. This difference is interesting given the sensitivity of measuring the aspect ratio especially in the presence of noise.

Hierarchical Classification

The minimum distance classifier was used as the main classification method. Table 6 presents the mean values of the descriptors as they apply at each node of the decision tree. These values are used to represent the prototypes from each class. The aspect ratio was used to discriminate between 1–D and 2–D distresses, the angle to classify 1–D distresses into longitudinal or transverse cracking, and the density and the inertia ratio to classify 2–D distresses into alligator and block cracking.

TABLE 3 ESTIMATION OF LOGIT MODEL PARAMETERS (*t*-STATISTICS IN PARENTHESES): $\rho^2 = 0.59$, $\bar{\rho}^2 = 0.38$

Distress Type	Inertia Ratio		Density		Angle	
	Relaxation	Regression	Relaxation	Regression	Relaxation	Regression
Block	-3.84 (-1.65)	-2.75 (-1.48)	9.81 (0.58)	7.67 (0.37)		
Longitudinal	-118.88 (-1.49)	-136.71 (-1.28)	86.89 (1.50)	104.96 (1.36)	1.01 (0.58)	0.75 (0.58)
Transverse	-112.80 (-1.64)	-141.05 (-1.79)	140.84 (2.22)	209.27 (2.35)	-8.86 (-1.71)	-8.99 (-1.52)

TABLE 4 LOGIT CLASSIFICATION RESULTS FOR RELAXATION (PERCENT CORRECTLY CLASSIFIED IN PARENTHESES)

Distress Type	Total Number	Classified as			
		Alligator	Block	Longitudinal	Transverse
Alligator	11	10 (91%)	1	0	0
Block	7	4	2 (29%)	0	1
Longitudinal	2	0	0	2 (100%)	0
Transverse	8	0	1	0	7 (87%)

TABLE 5 LOGIT CLASSIFICATION RESULTS FOR REGRESSION (PERCENT CORRECTLY CLASSIFIED IN PARENTHESES)

Distress Type	Total Number	Classified as			
		Alligator	Block	Longitudinal	Transverse
Alligator	11	11 (100%)	0	0	0
Block	7	4	2 (29%)	0	1
Longitudinal	2	0	0	2 (100%)	0
Transverse	8	0	0	0	8 (100%)

TABLE 6 FEATURE VECTOR AT THE NODES OF THE CLASSIFICATION

	INERTIA RATIO		ANGLE°		ASPECT RATIO		DENSITY	
	Relax.	Regr.	Relax.	Regr.	Relax.	Regr.	Relax.	Regr.
1-D	0.021	0.020			0.23			
2-D	0.290	0.331			0.82			
Longitudinal			85.4	85.1				
Transverse			7.4	2.4				
Alligator					0.87	0.87	0.0272	0.0212
Block					0.76	0.76	0.0262	0.0216

The results of the classification are presented in Table 7. The classification performed well at the top of the tree with 96 percent classification accuracy between 1–D and 2–D distresses. The only misclassification came from the same block-cracking image that is consistently classified as transverse cracking for reasons that will be explained in the next section. Similarly, the distinction between longitudinal and transverse cracking was accurate. Most of the misclassifications occur in the treatment of block cracking. If the angle is added as a third descriptor in the feature vector (for classifying 2–D distresses), the results become identical to the simultaneous classification (as expected). However, it is not clear what are the physical characteristics of the images that the angle captures to provide the higher accuracy.

To complete the analysis, and because the most difficult aspect of the classification seems to be the distinction between alligator and block cracking, the logit model was also used for the classification of 2–D distresses. The logit approach, using inertia and density as components of the utility functions, slightly improved the results obtained by the minimum distance classifier by assigning correctly more images with alligator cracking. The misclassifications are again concentrated around block cracking. The addition of the angle in the utility function improved the classification accuracy even more; all alligator cracking images were correctly classified, whereas four of the block cracking images were misclassified as alligator cracking. Overall, this approach of using the decision tree and combining different classification methods at each node provides great flexibility and efficiency and is most promising.

TABLE 7 TREE CLASSIFICATION RESULTS FOR REGRESSION AND RELAXATION (PERCENT CORRECTLY CLASSIFIED IN PARENTHESES)

Distress Type	Total Number	Classified as					
		1-D	2-D	Longitudinal	Transverse	Alligator	Block
1-D	10	10 (100%)	0				
2-D	18	1	17 (94%)				
Longitudinal	2			2 (100%)	0		
Transverse	8			0	8 (100%)		
Alligator	11					9 (73%)	2
Block	6					4	2 (33%)

ANALYSIS OF RESULTS

It is important that the main sources of error in the results presented in the previous section be examined and analyzed in detail. To provide a better understanding of the effectiveness of individual features used in the analysis and the major sources of error, the two-dimensional plots of inertia ratio versus density are shown in Figures 4 and 5 for both relaxation- and regression-segmented images. (Each distress observation is represented by the first letter of the distress group to which it belongs.) The means of the inertia ratio for 1-D and 2-D distresses differ by a large margin, and there is little overlap between the two classes. There is no 1-D distress with inertia ratio greater than 0.10. However, several 2-D distresses have low inertia ratios.

Density does not appear particularly useful for distinguishing between alligator and block cracking. The mean values of the density for the two distress types differ only slightly for the relaxation segmented images (0.0272 for alligator versus 0.0262 for block cracking) and for regression thresholded images (0.0212 for alligator versus 0.0216 for block cracking), and the overlap is clearly demonstrated in Figures 4 and 5. It is not clear whether the density is a geometrical feature with low discriminatory power or that other factors have contributed to its poor performance.

Detailed examination of the images that were misclassified and images whose descriptor values were outliers suggested the following possible sources of error and external factors that contribute to the poor performance of some of the descriptors:

1. Segmentation. Some images in their binary form had representations that were drastically different from their original shape. The main reason for their appearance is that after segmentation and noise removal the distresses are fragmented. They consist of a large number of individual segments without clear connectivity. An example of this is shown in Figure 6. Figure 6a is the original image of an alligator crack of high severity. The relaxation-segmented version of this image after noise removal as shown in Figure 6b has lost a substantial part of the distress outline, making the original distress pattern hard to recognize. Similarly, it is difficult to recognize the alligator crack in the regression-thresholded image in Figure 6c (although fewer segments are missing). The value of the inertia ratio for the relaxation-segmented image was 0.205, whereas for the regression thresholded version the value was 0.279; both these values are below the average for 2-D distresses. It is possible that the segmentation method itself has contributed to the poor appearance of some of the images examined below.

2. Hardware. The naturally low contrast between distresses and background is a possible explanation for the fragmented binary images. Furthermore, it has been observed (in the data set) that the missing segments in the binary images usually correspond to distress components that are aligned with the direction of movement. As Figure 7a shows, the longitudinal components of the block cracking are faint compared to the

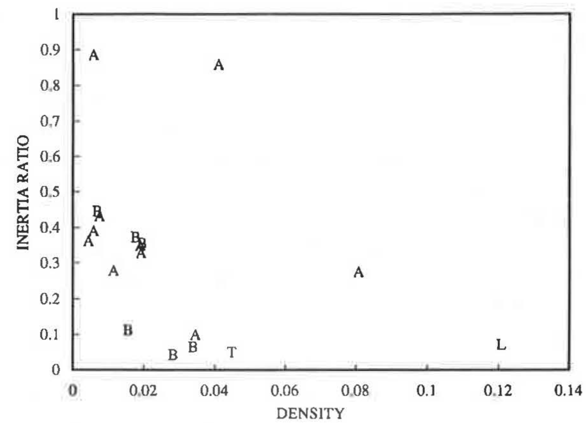


FIGURE 5 Inertia ratio versus density (regression).

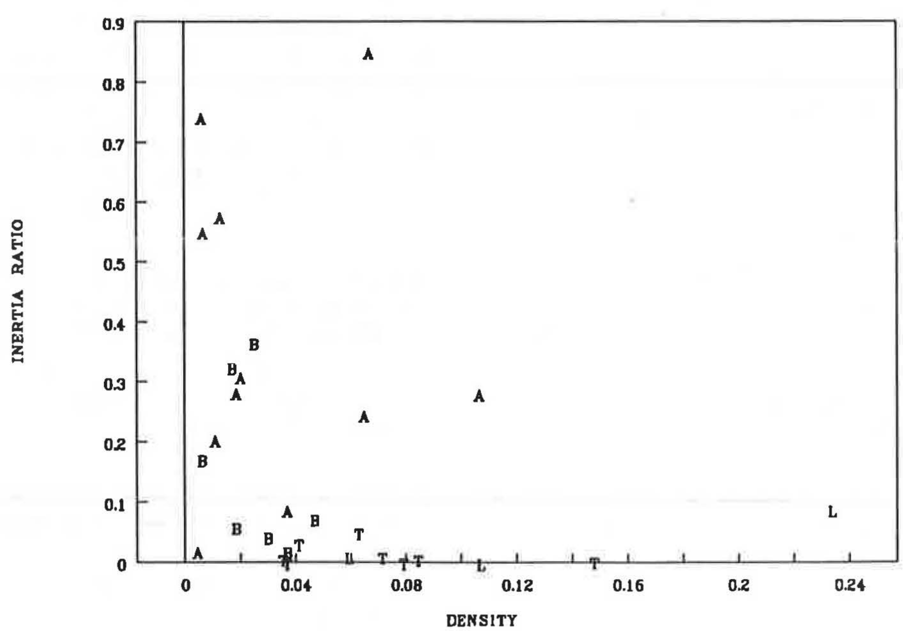
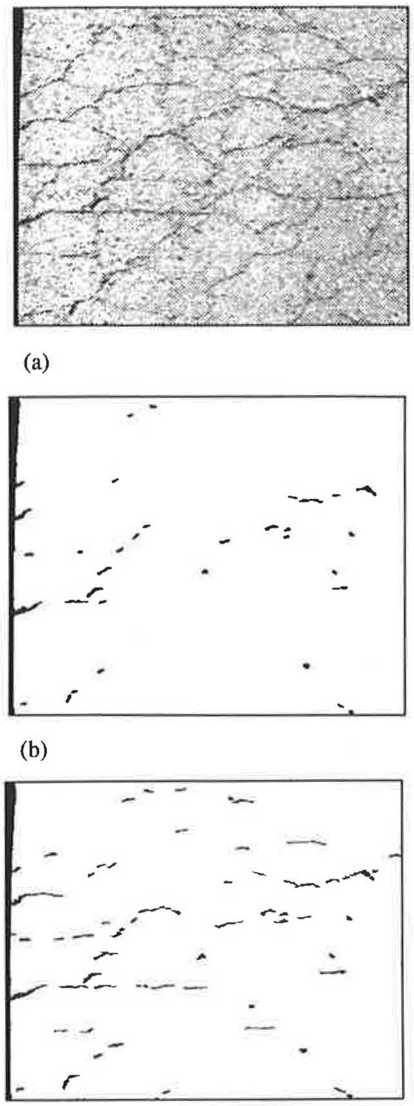


FIGURE 4 Inertia ratio versus density (relaxation).

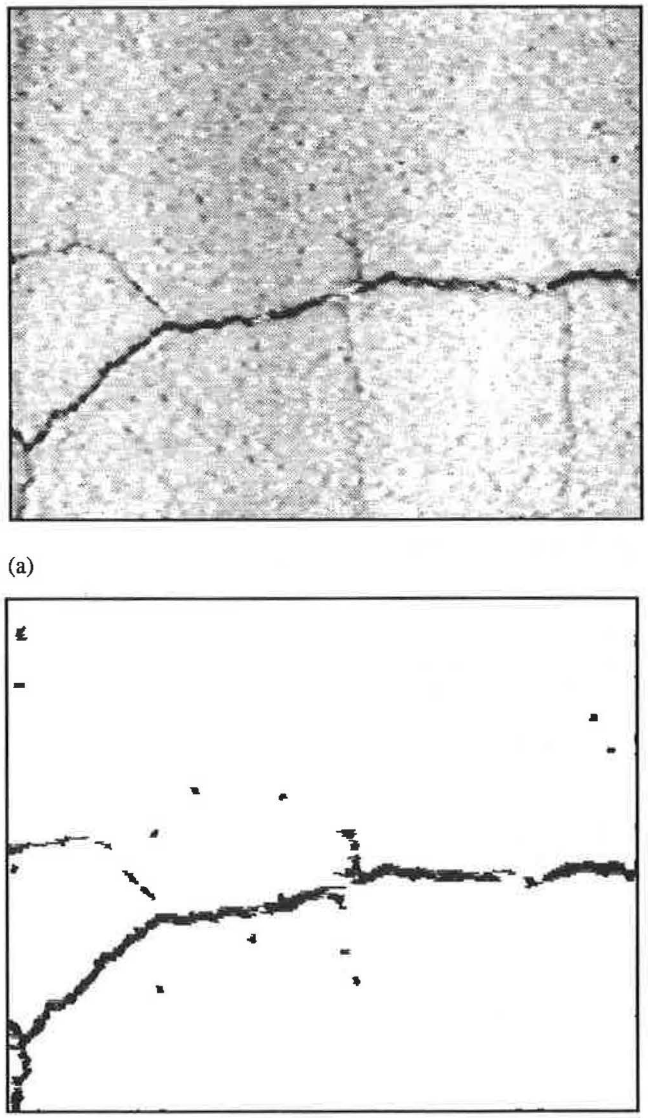


(a)

(b)

(c)

FIGURE 6 Example of poor segmentation: (a) alligator cracking, (b) segmentation by relaxation, and (c) segmentation by regression.



(a)

(b)

FIGURE 7 Example of possible hardware effects: (a) block cracking, and (b) segmented by regression.

transverse ones. As a result, the regression thresholded image shown in Figure 7b contains the transverse components of the distress but not the longitudinal ones. The effect of this dominance is obvious in the value of the inertia ratio for the distress, which is only 0.043. Hence, this image is consistently classified as transverse cracking and it is difficult even for the most sophisticated segmentation algorithms and statistical methods to analyze it correctly. It is possible that nonuniform illumination or the particular hardware configuration used contribute to the reduced contrast in the direction of travel.

Finally, it should be pointed out that the sample size, although small, is probably the size one would expect to have available in practice for training purposes. The longitudinal distress class with two representatives is the group with the smallest sample size and this may raise questions with respect to the validity of the results. However, it is clear from the analysis that longitudinal and transverse cracking have similar characteristics (except the angle of inclination) and may be treated as one class (i.e., linear cracking, with a total of 10 members). The angle of inclination then suffices to differentiate between longitudinal and transverse cracking, as was demonstrated in the hierarchical approach. Because angle of inclination is such a powerful descriptor, the small sample size associated with longitudinal cracking does not create any problems in interpreting the results.

CONCLUSIONS

On the basis of the analysis presented in the previous sections, the following conclusions can be drawn:

- The results obtained are promising and suggest that accurate interpretation of pavement distress images is possible.

It should be pointed out that distress-free images were not included in the data set; because these images are easily identified, incorporating them into the analysis would increase the classification accuracy significantly.

- The two segmentation methods tested (relaxation and regression thresholding) produce similar classification results. Hence regression may be preferred over relaxation because of its simplicity and computational efficiency.
- Simultaneous and hierarchical classification provide similar results, but hierarchical classification has an advantage over the simultaneous approach because of its flexibility.
- Angle and density seem to capture the expected characteristics of the various distress classes. Inertia ratio, when used with the minimum distance classifier, failed to differentiate between 1–D and 2–D distresses. However, it performed comparably to the aspect ratio when used with the logit model.
- The classification method based on the logit model produced more consistent and robust results and with the same or higher accuracy than the minimum distance classifier.
- From the various distresses examined, block cracking appears to be the most difficult to classify—with the geometrical descriptors and method used in the research. On the other hand, images with alligator cracking were correctly classified in most cases (with 100 percent accuracy when the logit model was used). Given the importance of alligator cracking in the evaluation of pavements, this result is significant.

Finally, several potential areas of further research have been identified:

1. Segmentation. Because of the characteristics of pavement images discussed earlier, the segmentation method used was unable to extract the full object. As a result, several binary images were fragmented. Although it is possible that some of these problems are hardware related, improving the quality of the binary images (removing noise and connecting distress fragments) may improve some of the statistics in the feature space and increase their discriminatory power. It is therefore important to examine methods that can be used after the initial segmentation is completed to restore the connectivity of the binary images.
2. Feature Vector. The feature vector used for the classification approach was based exclusively on geometric characteristics of images under consideration. However, as the analysis indicates, additional features, which capture differences other than those of shape, may be needed for reliable differentiation among the various distress types (especially block cracking). For example, the distance of a distress from the wheelpaths can be computed and used as a feature. This may help to distinguish between load-associated types of distresses such as alligator cracking and block cracking (which is similar in shape). Other statistics that may prove useful include textural descriptors and edge detectors. These additional statistics will be most useful in differentiating between the two classes when the majority of the misclassifications have occurred, namely for alligator and block cracking.
3. Classification Methods. The fact that the more advanced statistical method, based on the logit function, provided similar results, indicates that for improved accuracy more emphasis should be placed on developing more appropriate feature vectors, rather than using more elaborate classification techniques. Once such a vector is developed, various methods may be evaluated further, if necessary.
4. Highway Engineering Knowledge. More knowledge from the highway and pavement maintenance domain should be incorporated in the process. For example, as mentioned earlier, the distance of the location of the distress with respect to the wheelpath could be used as descriptor. It is also important to determine the levels of accuracy for measuring the various distresses that are needed for a practical pavement management system and to develop a quantification of the cost of misclassification on the basis of its effect on the maintenance process. Such parameters can then be used in the classification methodology to minimize misclassification cost (instead of error). The classification hierarchy suggested facilitates the incorporation of such parameters. Each pavement image also usually covers a small section of the pavement. Furthermore, images are analyzed independently of each other. Hence, there is important spatial information that is being ignored during the process. For example, a distress in the image may be identified as transverse cracking, whereas in reality it may be part of block cracking. However, this can only be identified if more than one pavement image is examined together. Hence, by looking at the problem from a macroscopic point of view and including spatial information, the classification task may be improved.
5. Transferability. An important future research activity should be the investigation of the transferability of the estimated parameters from system to system and from pavement to pavement. Transferability is a desirable property because it can greatly simplify the implementation of the methods suggested here and facilitate (if necessary) real time operation.

SUMMARY

Methods and algorithms for the automatic analysis of pavement images were presented with emphasis on evaluating (a) algorithms for segmentation of pavement images, (b) geometrical descriptors for characterizing the various distress classes, and (c) alternative classification methods and approaches. The results are promising and indicate that the task of automating the analysis of pavement images is feasible. Various issues associated with problems were discussed and directions for further research were identified.

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