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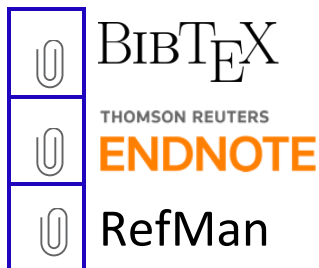
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HYBRID HUMAN-ARTIFICIAL INTELLIGENCE APPROACH FOR PAVEMENT DISTRESS ASSESSMENT (PICUCHA)

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ABSTRACT

The pavement surface condition assessment is a critical component for a proper pavement management system as well as for pavement rehabilitation design. A number of devices were developed to automatically record surface distresses in a continuous survey mode, but the software required for automatic distress identification remains a big challenge. In this study, a new method named PICture Unsupervised Classification with Human Analysis (PICUCHA) is proposed to circumvent many of the limitations of existing approaches, based on a combination of human and artificial intelligence. It was designed from scratch to be capable to identify sealed and unsealed cracks, potholes, patches, different types of pavements and others. The self-learning algorithms do not use any distresses predefinition and can process images taken by cameras with different brands, technologies and resolution. This study describes some key aspects of the new method and provides examples in which PICUCHA was tested in real conditions showing accuracy up to 96.9% in image pattern detection and classification.

KEYWORDS

Pavement Survey, Pavement Evaluation, Artificial Intelligence, PICUCHA Method

INTRODUCTION

The pavement surface condition is a very important indicator of the pavement quality. Its assessment in a timely fashion is a requirement for pavement management. In pavement rehabilitation design, it offers critical information to assist the design and decision making process of selecting optimal rehabilitation strategies. Over the last two decades, a number of devices were developed to assess the pavement surface condition by identifying distresses. One of the most popular technologies is based on an orthogonal (downward facing) picture taken with linear cameras mounted on moving vehicles. The Figure 1 shows one example of such a system that uses a line-scan camera and a laser illuminator, a device developed at the University of Texas at Austin [1]. Although the hardware systems are well developed in terms of acquiring good quality pavement images, the image analysis to reliably extract various distresses (i.e., data processing) remains a complex challenge.

Figure 1 - A line-scan camera-laser illuminator device on a pavement survey vehicle

Many methods have been proposed over the years for automated image analysis and pavement distresses detection. Salari and Yu developed an artificial intelligence approach by combing artificial neural network and genetic algorithms. An objective function was defined and maximized by applying information theory to choose the optimal threshold for segmentation, then the image's areas corresponding to distresses were represented by a matrix of square tiles; vertical and horizontal distresses and the total number of distresses were calculated and used to feed a neural network of distress type classification [2].

Lin and Liu used Support Vector Machine (SVM) – a topology of artificial intelligence similar to neural networks, for the specific purpose of detecting potholes on pavement images. The pavement texture was detected by using a histogram-based approach and a non-linear SVM was built to identify if the target region was a pothole. The experimental results show that the approach can achieve satisfactory results [3]. Chambon and others did an interesting review of different methods for image-processing for cracks detection and introduced a new methodology based on multi-scale extraction and Markovian segmentation [4].

To detect the pavement distresses on images, Ouyang et al. tried an approach based on filtering the images to remove the background, or pavement texture, and image enhancements, segmentation and Canny edge detection [5].

Ting and others used an approach based on k-means and classification algorithms to identify the pavement distresses on images [6]. The images were processed and filtered in order to keep only black-and-white pixels that were assumed as related to cracks. Then the images were grouped in clusters as distresses being detected by a decision-tree algorithm capable of recognizing horizontal, vertical, alligator and manhole-like cracks.

Nguyen and others detected cracks using a kind of conditional texture anisotropy to characterize and classify the pixels as "crack" or "crack-free" pixels. The idea is to detect variations of features, including noise, continuity, homogeneity and others. The authors claimed the method can detect also other patterns, like joints [7].

Zou and others developed the CrackTree, a system that detects pavement cracks and operates in three steps. Firstly, the pavement shadows were removed using a geodesic algorithm, then a crack map was built based on probabilities with a tensor analyser connecting the crack fragments according to the proximity and continuity and, finally, a recursive tree-edge pruning was used to identify the cracks [8]. Wang and others focused on the detection of micro-cracks on digital pictures and tested different methods to pre-process images to identify the best to detect micro-cracks, and proposed a way to remove shadows [9].

Article no. 13

THE CIVIL ENGINEERING JOURNAL 2-2017

Huidrom and others proposed a set of different processing techniques supported by heuristically derived decision logic to detect and quantify cracks, potholes and patches. The new method was developed using the OpenCV library, and showed it robustness and suitability for pavement management on Indian roads [10].

In Spain, Gavilán and others proposed a method that took a sequence of steps to remove the pavement texture, joints, sealed cracks and white paintings before crack detection with a multiple directional non-minimum suppression. Then, they connected the seed cracks based on a large set of parameters, and classified pavements into the ten types used in Spain based on support vector machine (SVM). They customized different parameters for cracks detection according to the type of pavement [11].

Radopoulou and others worked around an approach to detect patches on pavement images using filtering and histogram equalization to enhance the images, and a morphological process to detect patches [12].

Despite of the efforts made in developing these many procedures, most of them are still incapable of dealing with variations in pavement types, texture, lighting, etc. A small change in the pavement color, texture or presence of shadows could make the approach faulty, leading to a poor accuracy. In this study, we proposed a new approach called PICture Unsupervised Classification with Human Analysis (PICUCHA). PICUCHA offers a new way to look at the problem and handle the data by combining the computer capabilities in mass data analysis and the human flexibility in feature identification on images. This study is an extension of previous developments on artificial intelligence applied for pavement engineering, including pavement management with genetic algorithms [13], pavement modeling with neural networks [14] and a new modelling concept called "aside failure criteria" [15], among others.

A study to evaluate the PICUCHA method's accuracy while dealing with images at different resolutions was completed and suggests that images with a transverse resolution of 1.24 mm/pixel or better (2900 pixels for a 3.6 m wide lane) may be the ideal for the pavement distresses detection [16], that is a relevant information to be considered at the time of purchase an equipment for pavement survey as well as a reference for camera developers and integrators. In another study PICUCHA was tested with area-scan cameras, strobe lights and dark pavement. That is a challenging situation because on dark pavements is especially hard to distinguish between good pavement and distresses, and the type of camera and lights generate images with optical distortions and illumination joints that should be separated from regular pavement and distresses. PICUCHA could perform the analysis without problems and the final distresses assessment was made according to the Lithuanian standards. No images pre-processing was required [17].

THE PICTURE UNSUPERVISED CLASSIFICATION WITH HUMAN ANALYSIS METHOD (PICUCHA)

The PICUCHA approach was designed to circumvent limitations of existing procedures and handle most of the patterns registered on images, distresses or not, including good pavement, raveling, complex or isolated cracks, block or alligator cracks, sealed cracks, patches, potholes, painted horizontal signings, like white or yellow strips, reflective signs attached to the pavement, drainage devices, embedded inductive loops, joints, asphalt bleeding, or any combination of two or more of such patterns, among others. It can analyze road sections with mixed pavement types, like asphalt and concrete, with any kind of surface texture, color or pattern, including anti-slippery strips or cuttings, and with the presence of complex or solid shadows. It can even detect objects left over the pavement surface and visible on the pictures. The larger the number of patterns, the larger will be the number of groups.
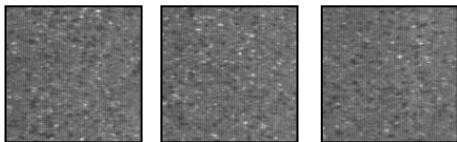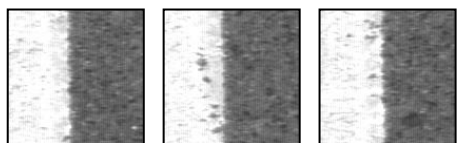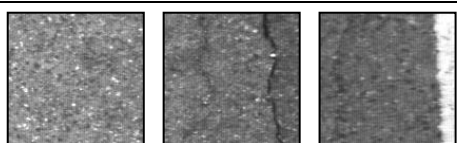
This procedure is divided in few simple steps. First, the digital pictures are sliced into cells and submitted for classification with an algorithm. Secondly, a human pavement expert manually analyses selected cells from each group and decide what kind of patterns and distresses are present. Finally, the expert's decisions are expanded to all the cells and images in the dataset.

The pictures should be technical orthogonal ("downward facing") images taken in the field with any device technology or brand (line-scan, regular shooter, LCMS, …) and any source of illumination (laser, incandescent, LED, …). Another study following PICUCHA method [16] suggests the ideal image resolution will have at least 2900 pixels over the lane width, but the method is capable to deal with images at any size and resolution, like 512 x 2048 or 2048 x 2048 pixels, even if taken by old cameras. The minimum acceptable image resolution is that one that allows a clear identification of the desired pavement distresses by a human eye. The slicing is done by breaking them down to smaller pieces called "cells". A 512 x 2048 pixels picture can be sliced, for example, into 64 cells with 128 x 128 pixels each one, but cannot be sliced into cells with, for example, 150 x 150 pixels, because that will leave part of the image uncovered.

The algorithm is a type of feedforward artificial neural network following the adaptive resonance theory and capable of producing a discretized representation of the input data, especially modified for this purpose [18] [19]. It is different from other artificial neural network because it uses a neighborhood function to preserve the topological properties of the input space and may operate in different modes, making them especially useful for data visualization, organization and classification.

The classification has the purpose of grouping together cells showing similar patterns. A homogeneous group will have all cells showing the same characteristics, while a non-homogeneous one will have cells showing different characteristics. Ideally, all groups will be homogeneous leading to a pattern classification accuracy of 100%. The Table 1 shows some examples of groups regarding homogeneity and the Figure 2 shows a flowchart showing the PICUCHA methodology main steps for image analysis, data processing and report generation.

Table 1 - Examples of homogeneous and non-homogeneous groups

Group type	Group characteristics	Cells' patterns		
Homogeneous	Good pavement			
Homogeneous	Good pavement with white strip			
Non-homogeneous	Mixed, including good pavement, cracks and white strip			

1	**Field survey** The field survey is done with any equipment capable to take downward facing pictures. The PICUCHA algorithms can process images taken with any device brand or technology including: • Line scan or regular shooter camera, laser crack measurement systems (LCMS) or other; • With laser, incandescent, LED or other types of lamps, or just natural illumination; and, • Images with any size and resolution. The higher the resolution and overall image quality, the better will be the final result.
2	**Key patterns identification** A special PICUCHA algorithm will analyze all images to identify and extract the key patterns. There is no predefinition of distresses or limitations, the algorithm can learn by itself and deal with any kind of pattern existing in a given image set.
3	**The human pavement expert analysis** The key patterns are analyzed by a human pavement expert that will describe the distresses and other desired characteristics with base on any standard or manual for distresses assessment. This procedure avoids the problem to rely just on software tools and keeps the human expert on top of the process.
4	**The human pavement expert analysis expanded to all images** The human pavement expert description is used to re-feed the algorithms that will expand such decisions to all the images in the given set, generating the final report.

Figure 2 - Flow chart of PICUCHA method's main steps

EXPLORING THE PICUCHA CLASSIFICATION ACCURACY FOR TWO DIFFERENT CELL SIZES

The cell classification is the most critical step in PICUCHA and the cell size is one of the most important variables in this process. A good cell classification will have direct impact on the overall accuracy of the distress assessment procedure. The ideal cell size may change from one set of images to another. Variation in cell size and its impact on accuracy is further explored in this study.

Figure 3 shows the image used in this study. It has 2048 x 512 pixels and 256 gray scale color scheme, covering an area of approximately 3.6 x 0.9 meters, that are the characteristics of the most widely used cameras nowadays, with line scan technology. The picture shows different patterns including raveling, good pavement, cracked pavement and a white strip. Figure 4 shows the pixels coordinates represented as a 3D mesh of points with artificial colors where the pixel color distribution over the picture surface can be seen.

The ideal cell's size will change according to the camera resolution, camera technology, illumination source and characteristics of the pavement distresses. The cell cannot be that big that will show too many patterns and distresses together in the same cell, and must be large enough that a human eye can identify the distresses while observing an isolated cell. Another important criterion is to choose a size that will fully cover the image area with cells with the same dimensions, without gaps or overlaps, or leaving parts of the image uncovered. A small-scale test with different size for cells may be used to identify the best cells dimensions for every major picture set. In this study, the PICUCHA approach accuracy was tested for the two different cell sizes that meet such criteria. Figure 3 was sliced in cells of 64 x 64 pixels for the first set, and in cells of 128 x 128 pixels for the second set. A human analysis was done for the set with the best pattern classification.

Article no. 13

THE CIVIL ENGINEERING JOURNAL 2-2017

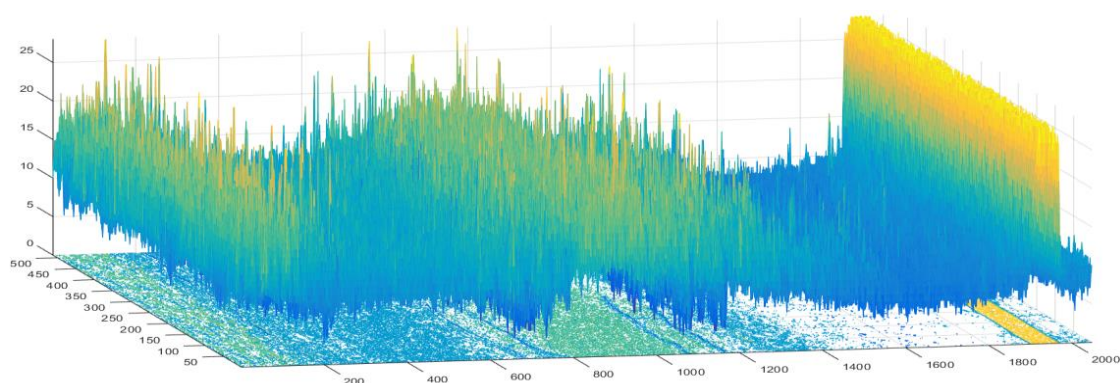*Figure 3 - Analyzed pavement picture with 2048 x 512 pixels*

Figure 4 - The 3D mesh of points representation with artificial color for Figure 3

The 64-pixel cells classification

The algorithm was executed and the 64-pixel cells were classified into 21 groups (256 cells in total), shown in Figure 5 over the source image. Figure 6 has the groups' analysis regarding homogeneity, showing that among the 21 groups, 4 are non-homogeneous, with a total of 55 cells diverging of the group predominant characteristics.
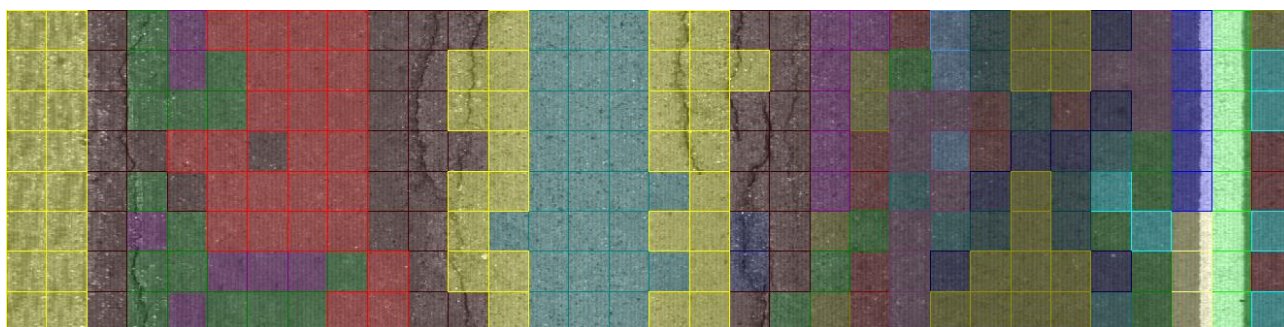

Figure 5 - Neural networks grouped the 64-pixel picture cells in 21 groups
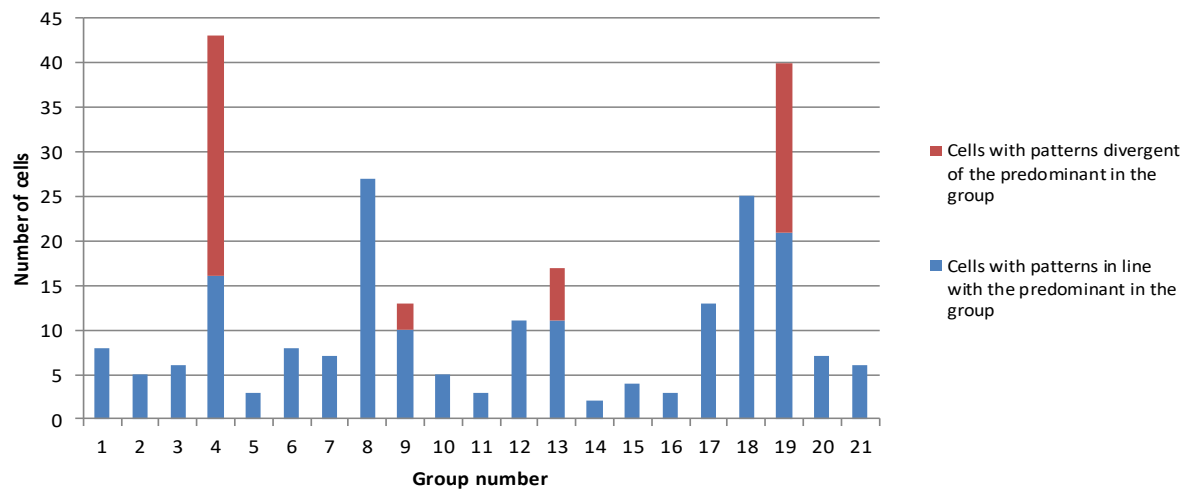
Figure 6 - Homogeneity analysis for 64 pixel cells (total of 256 cells)

The 128-pixel cells classification

The algorithm was executed for the 128-pixel cells set generating 16 groups, shown over the original image in Figure 7. Among a total of 64 cells just 2 were found with characteristics divergent from the group predominant (Figure 8).
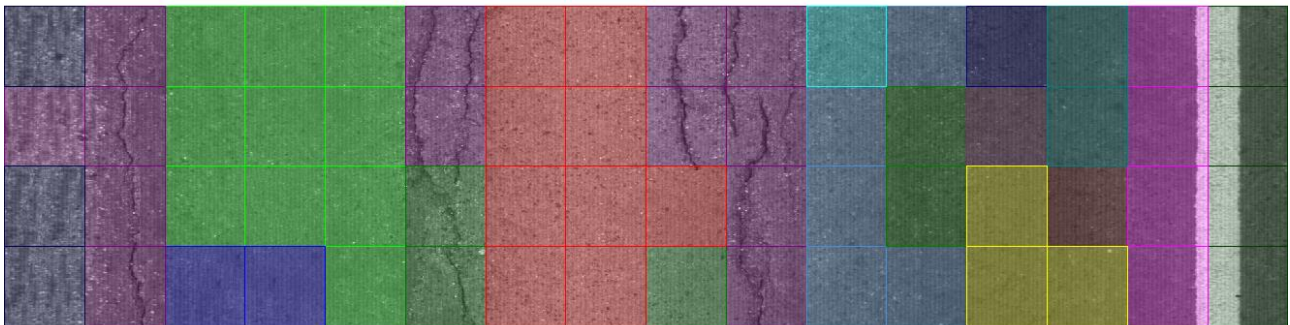

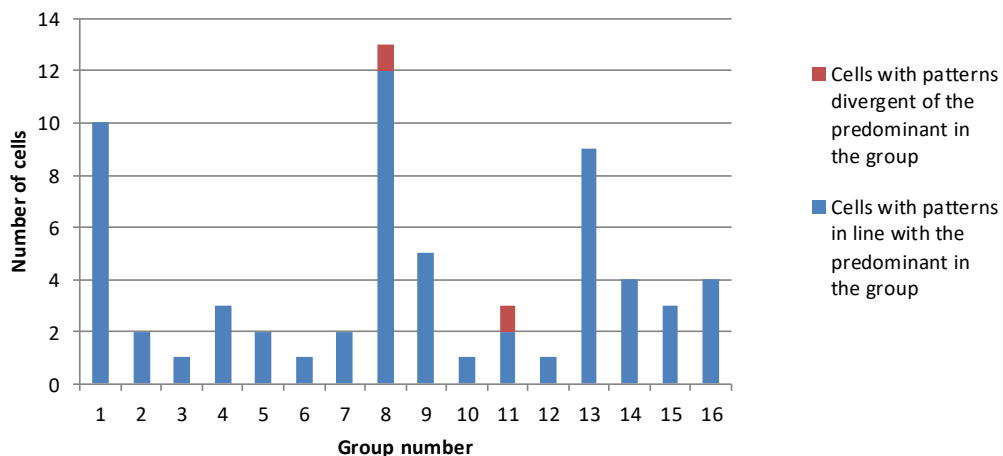*Figure 7 - Neural networks grouped the 128-pixel picture cells in 16 groups*

Figure 8 - Homogeneity analysis for 128-pixel cells (total of 64 cells)

Article no. 13

THE CIVIL ENGINEERING JOURNAL 2-2017

Table 2 - Cells classification and clustering results

Simu-lation	Cell size (pixels)		Total number of cells	Number of generated groups	Groups		Number of cells on the...		Cells with relevant divergence to group predominant characteristics		Classification Accuracy (%)
	X	Y			Homo-geneous	Non-homo-geneous	smallest group	largest group	Number of cells	(%)	
1	64	64	256	21	17	4	2	43	55	21.5	78.5
2	128	128	64	16	14	2	1	13	2	3.1	96.9

Neural networks classification accuracy

The classification accuracy criterion is based on the number of cells with patterns diverging of the predominant one in its respective group, for all groups, and corresponds to the work done by the neural networks classifications only. It does not include mistakes or corrections and improvements done by the human pavement expert, that may lead to a lower or higher final accuracy. For the 64-pixel cells, the classification accuracy found is 78.5%, with 55 of the 256 cells showing patterns different of the one predominant in the respective cluster. The 128-pixel cells set is showing better accuracy, with just 2 among 64 cells showing divergent patterns, representing an accuracy of 96.9%. The classification key data, for both sets, is shown in Table 2.

The human made analysis for the 128-pixel cells set

The key patterns of the highest accuracy picture set were hand analyzed by a human pavement expert to identify what type of distresses or characteristics were present. It is normal and expected to find different groups showing the same characteristics. This happens because a characteristic, like good pavement, may be present with different visual characteristics (e.g. different texture or color), which will lead the neural network to generate different groups. Figure 9 shows the groups with the same patterns merged. In this step, the 17 clusters generated by the algorithm (see Figure 7) were reduced to 7; the two misclassified cells are identified with an "x".

The pavement expert analysis for the existing patterns is shown in Table 3. The patterns 6 and 7 were split into two for the proper calculation of the white strip area. Figure 10 shows the final consolidated results. The distresses may be assessed or consolidated according any standard, like the Manual SHRP-P-338 (Strategic Highway Research Program, 1993).
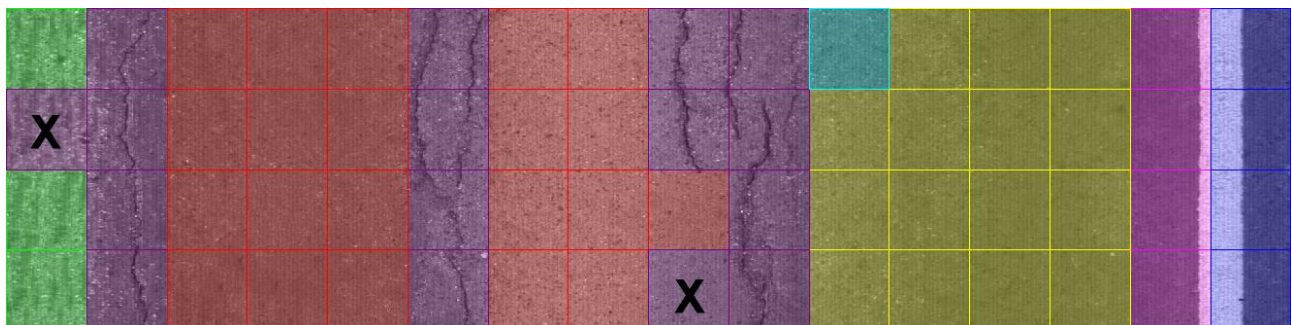

Figure 9 - Picture classification according to the patterns (misclassified cells are marked with "x")

Table 3 - Distresses and characteristics assessment

| Patterns (According to Figure 9)		Classification	Number of cells	Surface area	
				Total	Specific
1		Raveling	3	4.7%	4.7%
2		Good pavement	21	32.8%	32.8%
3		High severity cracks (Includes 2 misclassified cells marked with a "x" on Figure 9)	16	25.0%	25.0%
4		Medium severity cracks	1	1.6%	1.6%
5		Low severity cracks	15	23.4%	23.4%
6		Low severity cracks (80% of the cell surface)	4	6.3%	5.0%
		White strip (20% of the cell surface)			1.3%
7		Good pavement (60% of the cell surface)	4	6.3%	3.8%
		White strip (40% of the cell surface)			2.5%
		Total	64	100%	100%

Final Classification
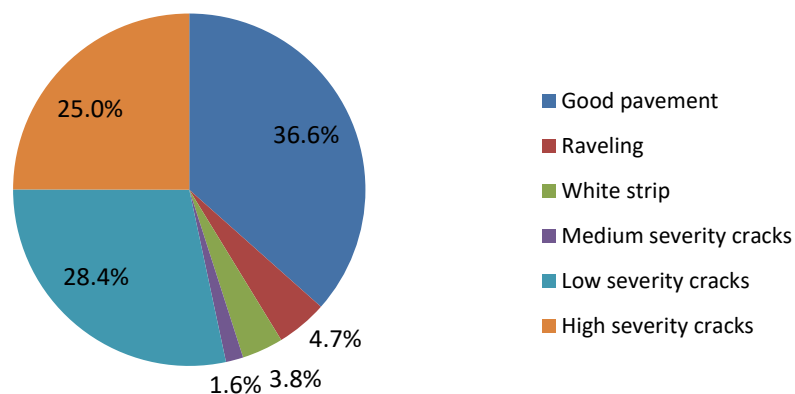
Figure 10 - Consolidated distress assessment results

CONCLUSIONS

A number of hardware devices available at commercial level are capable to register high quality and accurate images of pavement surface. Contrarily, methods and software required to process and analyze the images are not as abundant. In addition, they provide weak results in terms of accuracy and limitations in what they can reasonably detect; most confined to just crack detection, ignoring other important distresses and patterns.

The PICUCHA method is based on neural networks and models the problem in a different way. The problem setup and self-learning algorithms does not use any distresses or patterns predefinition, providing a procedure capable of dealing with almost any type of distress or characteristics identifiable by the human eye and different kinds of pavement surfaces. It can also process images taken with any type of camera technology or brand, with different kinds of surface illumination and any image size and resolution.

This study demonstrates the PICUCHA method's ability to classify different types of pavement distress by employing pattern recognition. This approach greatly simplifies the image analysis process by reducing the data analysis to small groups of different patterns peculiar to the dataset that can be accurately evaluated by a human pavement expert. The procedure then applies the pattern classification to the entire dataset to fully characterize and quantify the pavement surface.

The PICUCHA method provides a procedure in which the human pavement expert has the total control over the detection outcome and further classification and quantification of distresses. Purposefully, it preserves the subjective component found in normal pavement surface evaluations, in which despite of the standards, different human experts may identify distresses in different ways and severities. By preserving this subjectivity, the proposed method becomes easily adaptable to any condition which imagery data was collected, the type of pavement structure or road class, as well as different classification standard employed by the road authority for distresses assessment.

This study introduces and discusses the cell size issue and the concept of homogeneous groups. A practical example is provided to demonstrate the steps and considerations to slice a pavement surface image, the grouping result and the engineer input for the final distresses assessment. The image was successful sliced in different cells sizes and processed allowing the patterns classification with accuracy of 78.5% and 96.9% for the 64 and 128 pixels cells, respectively. Neural networks "see" the images in a similar way the human eye does. The cells with 128 pixels provide a higher accuracy because they have better characterized patterns that are easier to identify, distinguish and group than the 64 pixels cells, where different patterns can be confused more easily. The cells with 128 pixels and 256 gray scales contain 131072 bits of information (128 * 128 * 8) for the classification and grouping task, while the 64 pixels cells contain only 32768 bits of data.

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