IMPACT OF IMAGE RESOLUTION ON PAVEMENT DISTRESS DETECTION USING PICUCHA METHODOLOGY

Reus Salini[1], Bugao Xu[2] and Mena Souliman[3]

1 Neogennium Technologies, Florianópolis, Brazil; salini@gmx.net

2 The University of Texas at Austin, School of Human Ecology, Center for Transportation Research, Austin, United States of America; bxu@utexas.edu

3 The University of Texas at Tyler, Departments of Civil Engineering and Construction Management, Tyler, United States of America; msouliman@uttyler.edu

ABSTRACT

An accurate and regular survey of the road surface distresses is a key factor for pavement rehabilitation design and management, allowing public managers to maximize the value of the continuously limited budgets for road improvements and maintenance. Manual pavement distress surveys are labor-intensive, expensive and unsafe for highly-trafficked highways. Over the years, automated surveys using various hardware devices have been developed and improved for pavement field data collection to solve the problems associated with manual surveys. However, the reliable distress detection software and the data analysis remain challenging. This study focused on the analysis of a newly-developed pavement distress classification algorithm, called the PICture Unsupervised Classification with Human Analysis (PICUCHA) method, particularly the impact of image resolutions on its classification accuracy. The results show that a non-linear relationship exists between the classification accuracy and the image resolution, suggesting that images with a resolution around 1.24 mm/pixel may provide the optimal classification accuracy when using the PICUCHA method. The findings of this study can help to improve more effective uses of the specialize software for pavement distress classification, to support decision makers to choose cameras according to their budgets and desired survey accuracy, and to evaluate how existing cameras will perform if used with PICUCHA.

KEYWORDS

Pavement Engineering, Automatic Distress Detection, PICUCHA Method

INTRODUCTION

The pavement surface condition assessment provides the most important information for a proper pavement management as well as for pavement rehabilitation design. The manual assessments, common decades ago, are no longer viable for many reasons such as high costs, high labor demand, and high risks for staff on current trafficked highways.

Over the years different imaging technologies were developed or adapted for automated pavement surveys, including traditional cameras that take an image covering a rectangular area on every shot, line-scan cameras that take one single line of pixels on every shot, and 3D cameras that read one transversal lane profile on every shot. Despite the progress on the hardware used in the field survey, the distresses detection and analysis software for generating field data remains relatively underdeveloped.

Koutsopoulos and Downey developed an alternative procedure for automated classification of asphalt pavement distresses recorded in video or photographic films based on a model that described the statistic properties of pavement images. In addition to image enhancement and segmentation, the distresses were detected by searching for primitive blocks of pixels to detect different types of cracks [1].

Lin and Liu used Support Vector Machine (SVM), a topology of artificial intelligence to detect potholes in pavement pictures. The pavement texture was detected by using the histogram and a non-linear SVM was built to classify target regions into potholes or non-potholes. The experimental results showed that the approach could achieve satisfactory results [2].

Detecting potholes was also the subject in Koch and Brilakis' study. The images were first segmented into defect and non-defect regions using the histogram-based thresholding. The potential pothole shape was then approximated by utilizing morphological thinning and elliptic regression. The texture inside a potential pothole was then compared with the texture of the surrounding area to decide if it represented a pothole or not. The routine was implemented in MATLAB [3]. After the procedure was improved by using a vision tracker to reduce the computational effort and improve the detection and pothole counting [4].

An approach combining analytic hierarchy process (AHP) and fuzzy logic theory for pavement condition assessment was developed by Sun and Gu. AHP was used to determine a weight from a paired comparison matrix and an evaluation with fuzzy relations, combining the evaluation of five different indicators: roughness, deflection, surface deterioration, rutting and skid resistance. A maximum grade principle and a defuzzified weighted cumulative index were proposed to assess the condition of a road [5].

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, image enhancements, segmentation and Canny edge detection [6].

For distresses identification on concrete pavements, Tsao, et al. developed a rule-based vision system [7]. The system had a knowledge database with facts and rules to identify different types of distresses by gathering information on the input images and deciding the optimum sequence of operations for the processing.

Ting, et al. used an approach based on the k-means classification algorithms to identify the pavement distresses on pictures. The images were processed and filtered in order to keep only black-and-white pixels that were assumed as related to cracks. The images were then grouped in clusters as distresses being detected by a decision-tree algorithm capable of recognizing horizontal, vertical, alligator and man-hole-like cracks [8].

Rababaah, et al. did a comparison of different algorithms including genetic algorithms, multilayer perceptron and self-organizing maps subdivided in image processing, crack detection, crack representation and crack classification, and discussed the impact of the representation on the final classification [9].

Nguyen, et al. performed a cracks detection technique using a sort of conditional texture anisotropy to characterize and classify the pixels as "crack" or "crack-free" pixels [10]. The idea was to detect variations of features, including noise, continuity, homogeneity and others. The authors claimed the method could also detect other patterns such as pavement joints.

Puan, et al. developed an automated pavement imaging program (APIP) for pavement distresses assessment, capable of working with longitudinal, transverse and alligator cracks, and analyzing the crack severity by using a number of different algorithms [11].

Tsai, et al. took image segmentation as a kind of preprocessing for distresses detection and classification. Six different algorithms were used and evaluated with images taken near the city of Atlanta, USA, with varying lighting condition, shadows and cracks [12].

PICUCHA FOR PAVEMENT DISTRESSES ASSESSMENT

The PICture Unsupervised Classification with Human Analysis (PICUCHA) method is a new approach for pavement distresses assessment that combines the human flexibility to recognize patterns on imagens with the neural network ability to match patterns by similarity, expanding the (human) pavement engineer decisions over large image sets.

PICUCHA has been designed to circumvent the limitations commonly found on other methodologies such as the variations on the pavement color and texture, handling all the patterns registered on images, distresses or not. PICUCHA can detect good pavement, raveling, complex or isolated cracks, block or alligator cracks, sealed cracks, patches, potholes, painted horizontal signals, 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.

PICUCHA is capable of analyzing orthogonal images ("downward facing") taken in the field with any device technology (line-scan, area scan, laser crack measurement system [LCMS], …), different sources of illumination (laser, incandescent, LED, …) and different image dimensions such as 512 x 2048 or 2048 x 2048 pixels. The PICUCHA approach is structured in a few steps including field survey, key patterns extraction, key patterns analysis by a pavement engineer, and the engineer's decisions expansion to all the images in a given set, as shown in *Figure 1.*

The PICUCHA method is an extension of our previous developments on new methodologies and artificial intelligence applied for pavement engineering, including pavement management with genetic algorithms [13], pavement modeling with neural networks [14], the aside failure criteria that opens a new frontier of possibilities [15], and a deflection basin geometry analysis to calculate strains [16].

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 area-scan 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.

2 Key patterns identification

The images are sliced into cells (e.g. 128 x 128 pixels) and a special algorithm will analyze to identify and extract the key patterns. There is no predefinition of distresses or limitations, the self-learning algorithm 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 refeed the algorithms that will expand such decisions to all the images in the given set, generating the final report.

Figure 1 - Flow chart of PICUCHA Method's main steps

RELEVANCE OF CAMERAS AND IMAGE RESOLUTIONS

Over the years the companies developed different cameras technologies and other devices for pavement surface condition assessment with growing image resolutions. The most common are the area-scan cameras, line-scan cameras and laser crack measurement systems (LCMS). Those devices are available from different suppliers and integrators ("brands"), and can be purchased at different image resolutions. The camera type and resolution have a direct impact on the image quality and an even heavier relevance for the equipment's cost.

Area-scan cameras were the first generation of equipment for pavement survey. They are adaptations of general purpose cameras (*Figure 2.a*) and are notorious for its low cost. Some integrators assemble two cameras together for a higher resolution. This type of camera takes a rectangular image on every shot (e.g. 2048x512 pixels) that results in a number of problems, especially image distortions since some pavement areas are closer to the camera lens then others, and non-homogeneous illumination, because some areas of the pavement are closer to the illumination source then others. Those problems are especially visible when two or more images are assembled together and generate an extra challenge for the distresses detection by software. Area-scan cameras are not compatible with laser illumination, requiring many lamps that usually are strobe flashlights.

Line-scan cameras represent an advance in technology and image quality (*Figure 2.b*). As its name suggests, it takes one single line of pixels on every shot (e.g. 2048 x 1 pixels). Image distortions and illumination heterogeneity are minimal. The line-scanned pixels can be assembled together to generate a consistent and flat rectangular image. It is compatible with laser (beam) illumination in addition to incandescent, LED and others.

The laser crack measurement systems (LCMS) collect two different information at the same time: an image and a transverse profile (*Figure 2.c*). The image is usually a by-product for this equipment and its quality tends to be low. The analysis is performed by using the profile data to locate the cracks over the image. It is especially accurate to identify cracks and rutting. Some integrators install the LCMS together with line-scan cameras for a better image quality. Other integrators also install high accuracy accelerometers, allowing using the data for a kind of pavement topographical survey. This technology is relatively new and well-known for its high cost, which is frequently higher than one million dollar for a vehicle with a LCMS system.

(a) Area-scan camera (b) Line-scan camera (c) Laser crack measurement system (LCMS)

Figure 2 - Camera technologies for pavement surveys

Regardless of the camera technology, there is a consensus that, the higher the image resolution, the easier and more accurate the pavement distresses assessment will be. However, higher resolution implies in higher costs.

Frequently the resolution is improved by raising the number of cameras, e.g. two 2048 pixels resolution cameras are integrated to provide a final resolution of 4096 pixels. Up to eight cameras have been used together so far. Survey systems with higher resolutions are more expensive and complex from a technical perspective, with implications for integration, calibration, operation, data acquisition and storage, and maintenance. Thus, camera resolution is an extremely important factor to be taken in consideration at the time to choose a system for pavement surface survey. On the other hand, a software system capable to provide an accurate distresses assessment working with rather limited resolution images has the potential to make an important and positive impact for this industry, making it feasible to use affordable cameras and revitalizing the use of simple pavement survey systems.

This study explores the PICUCHA method performance for images with different resolutions. For this purpose an image at five different resolutions was tested and the method's error was evaluated regarding to how many cells were misclassified, i.e., how many cells were grouped together with cells showing different characteristics or distresses. The objective is concentrated on evaluating how the PICUCHA self-learning algorithms will perform on the grouping task only, without a final distresses description because it requires additional steps unwanted for this particular study.

PICUCHA ACCURACY AT DIFFERENT IMAGE RESOLUTIONS

An image taken with a line-scan camera with an original resolution of 2048 x 512 pixels, and covering an area of approximately 3.6 x 0.9 m (*Figure 3*), was downsized to the tested resolutions. Such image was chosen because it is representative of how PICUCHA performs. In addition it shows different kinds of patterns, including good pavement, raveling, cracks with different severities and a white strip. The 3D points mesh as well as the pixels decks with artificial colors for such image are shown on *Figure 4* and *Figure 5*, respectively. They are part of

PICUCHA intermediate steps for the data processing that are not the focus of this study.

All the image resampling was completed from the original image at full resolution (2048 x 512 pixels) to the required size using bicubic interpolation with a sharpness factor of 0.51, that is the most common method for digital image resizing [17], as shown on *Table 1.*

Figure 3 - Image with original resolution of 2048 x 512 pixels

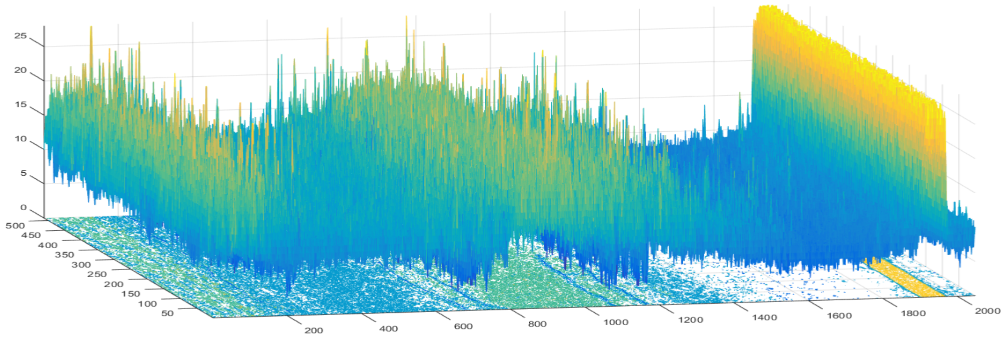

Figure 4 - The 3D mesh of points representation for the 2048x512 pixels image

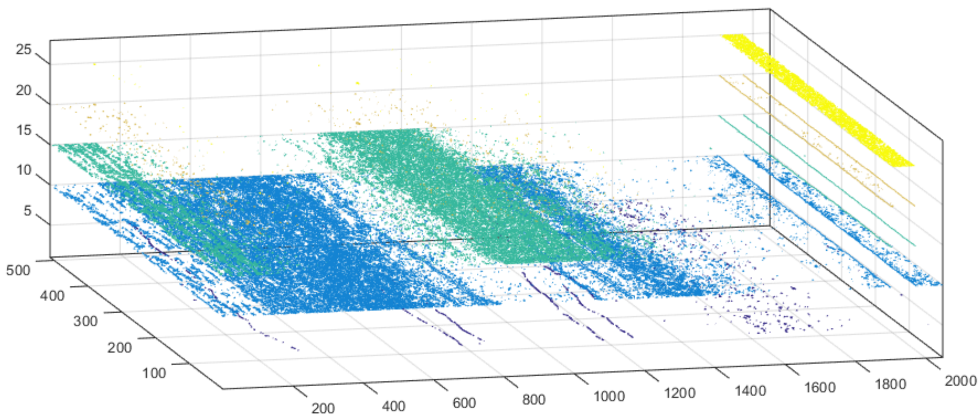

Figure 5 - The 3D pixel decks for the 2048x512 pixels image

Table 1 - Resolutions for the tested image

Original image size (pixels)		Reduction	Reduced image size (pixels)		Resolution (mm/pixel)
Horizontal	Vertical		Horizontal	Vertical	
2048	512	0.0%	2048	512	1.76
2048	512	12.5%	1792	448	2.01
2048	512	25.0%	1536	384	2.34
2048	512	37.5%	1280	320	2.81
2048	512	50.0%	1024	256	3.52

The image, at its five different resolutions, was submitted for classification using PICUCHA algorithms. To keep the test consistency and the image slicing to the same number of cells for every case, the cell size was reduced in the same proportion of the image resizing, as shown in *Table 2.* The classification results are shown in *Figure 6-10* where the generated groups can be seen. Because of the unsupervisied nature of this artificial intelligence approach the cells marked with the same color belong to the same group and should have the same pattern. The cells that do not attend that criteria, i.e., were included in a group with a different predominant pattern, represent the algorithm error and are marked with a "x". The identification of misclassified cells was performed by an experienced pavement engineer. In this study the colors are used only for the groups' identification and, because every image (*Figure 6-10*) represents a different processing started from the ground, same colors in different images may represent different patterns. Another situation that frequently happens is that the algorithms, while performing the self-learning, may decide to create different groups for cells with patterns that, from a human perspective, look similar. When this situation happens the (human) pavement expert analyst will, in the step 3 of this methodology (*Figure 1*), set that groups with the same description for the distresses accounting.

Table 2 - Number of misclassified cells according to the image resolution

Image size (pixels)		Resolution (pixels)	Cell size (pixels)	Total number of cells	Misclassified cells	Error (%)
Horizontal	Vertical					
2048	512	1048576	128	64	2	3.1%
1792	448	802816	112	64	5	7.8%
1536	384	589824	96	64	4	6.3%
1280	320	409600	80	64	7	10.9%
1024	256	262144	64	64	6	9.4%

As expected, the number of misclassified cells rose as the resolution dropped, but not in a linear way. At the highest resolution, 2048x512 pixels, the error was the smallest, with just two cells being misclassified among 64. At the lowest resolution, 1024x256 pixels, six cells were misclassified with an error rate of 9.4%. The largest error was found at resolution of 1280x320 pixels with seven cells misclassified, corresponding to an error of 10.9% as shown in *Table 2*.

Figure 11 shows the found errors graphically with a respective trend line and a prediction equation. On the basis of the trend line, the upper and lower limits can be plotted with a plus and minus standard deviation (3.0%), as shown in *Figure 12*. By extrapolating the upper limit, the ideal image dimension can be identified at a location near 2 megapixels where the theoretical error is zero. This dimension is equivalent to an image size of 2900x725 pixels, or a resolution of 1.24 mm/pixel.

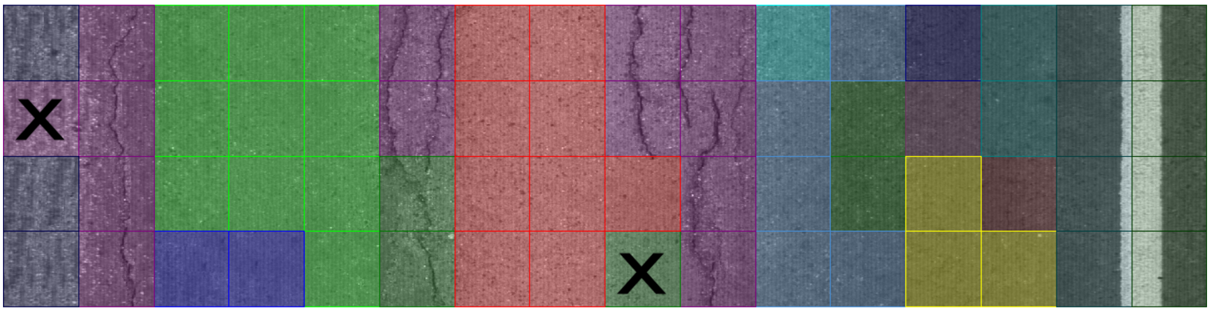

Figure 6 - Cells classification for the 2048x512 pixels image

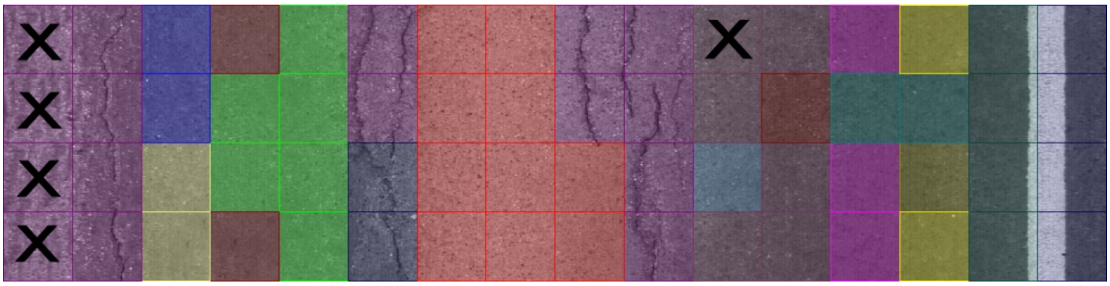

Figure 7 - Cells classification for the 1792x448 pixels image

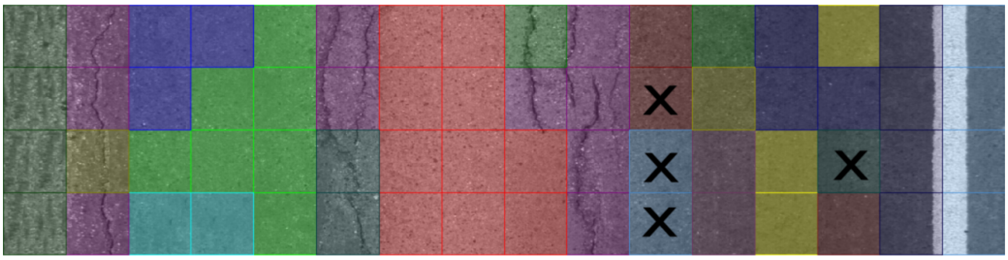

Figure 8 - Cells classification for the 1536x384 pixels image

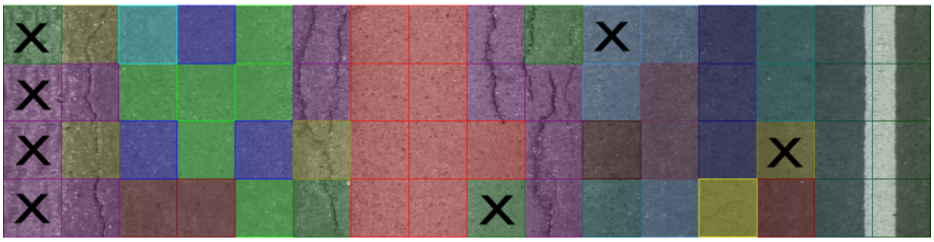

Figure 9 - Cells classification for the 1280x320 pixels image

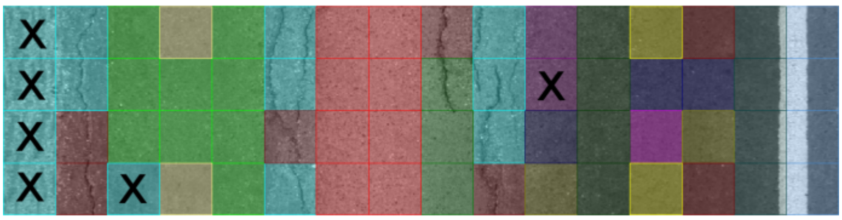

Figure 10 - Cells classification for the 1024x256 pixels image

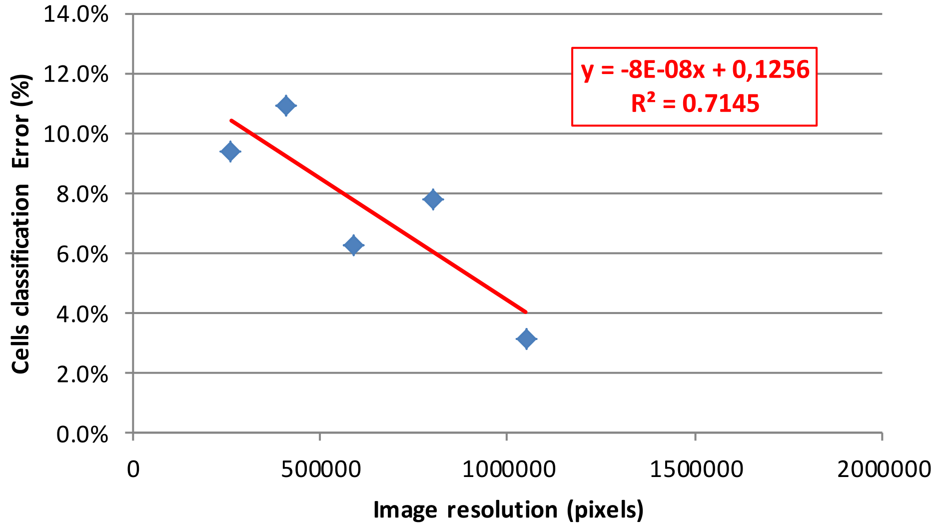

Figure 11 - Classification error according to the image resolution

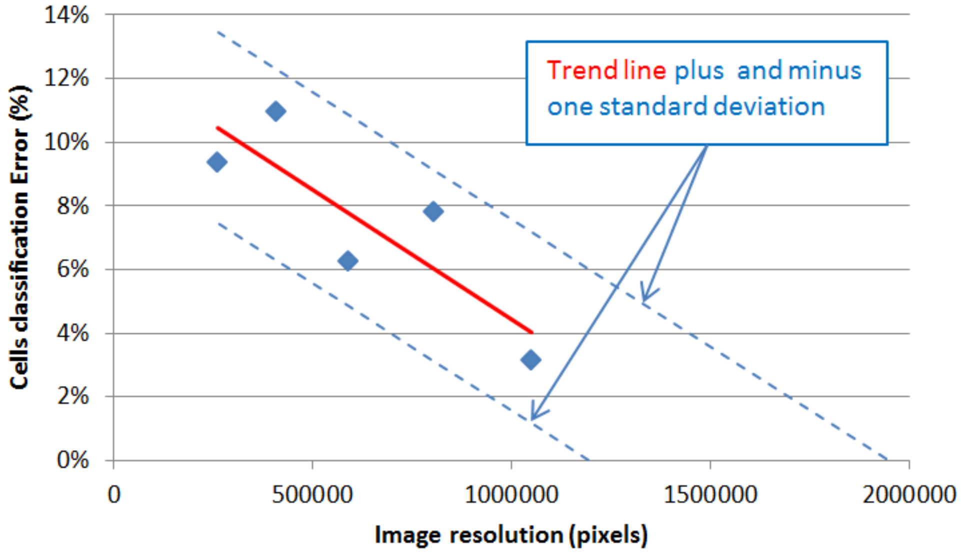

Figure 12 - Projection of ideal image resolution for PICUCHA method

CONCLUSIONS

The PICUCHA method can be used to properly handle and classify the image at all tested resolutions. The error expressed in the number of cells misclassified, i.e. classified in groups with different predominant characteristics, rose in a non-linear way when the image resolution dropped, but was relatively low in all cases. The minimum error was 3.1% for the image with the highest resolution (2048x512 pixels) and the maximum error was 10.9% for the image with 1280x320 pixels. The image with the lowest resolution (1024x256 pixels) had 9.4% of the cells misclassified.

The error trend line analysis suggests the optimum transverse image resolution should be more than 2900 pixels, i.e.,around 1.24 mm/pixel. Although this should not be assumed as a definitive parameter, it is a good resolution reference for selecting a camera system for pavement surveys when PICUCHA will be used for the analysis.

REFERENCES

[1] Koutsopoulos, H.N., Downey, A.B. 1993. Primitive-Based Classification of Pavement Cracking Images. J. Transp. Eng., 119 (3), p. 402–418.

[2] Lin, J., Liu, Y. 2010. Potholes detection based on SVM in the pavement distress image. Proc. - 9th Int. Symp. Distrib. Comput. Appl. to Business, Eng. Sci. DCABES 2010, p. 544–547.

[3] Koch, C., Brilakis, I. 2011. Pothole detection in asphalt pavement images. Adv. Eng. Informatics, 25 (3), p. 507–515.

[4] Koch, C. et al. 2013. Automated Pothole Distress Assessment Using Asphalt Pavement Video Data. J. Comput. Civ. Eng., 27 (4), p. 370–378.

[5] Sun, L., Gu, W. 2011. Pavement Condition Assessment Using Fuzzy Logic Theory and Analytic Hierarchy Process. J. Transp. Eng., 137 (9), p. 648–655.

[6] Ouyang, A. et al. 2010. Surface Distresses Detection of Pavement Based on Digital Image Processing. In: IFIP Advances in Information and Communication Technology. Nanchang, China, p. 368–375.

[7] Tsao, S. et al. 1994. Image-Based Expert-System Approach to Distress Detection on CRC Pavement. J. Transp. Eng., 120 (1), p. 52–64.

[8] Ho, T. et al. 2010. Pavement distress image recognition using k-means and classification algorithms. In: Computing in Civil and Building Engineering, Proceedings of the International Conference (Editor: W. Tizani). Nottingham, UK: Nottingham University Press, p. 73–78.

[9] Rababaah, H. et al. 2005. Asphalt Pavement Crack Classification: A Comparison of GA, MLP, and SOM. In: Genetic and Evolutionary Computation Conference (GECCO'2005) (Editor: F. Rothlauf). Washington, D.C., USA.

[10] Nguyen, T.S. et al. 2010. Pavement Cracking Detection Using an Anisotropy Measurement. In: 11ème IASTED International Conference on Computer Graphics and Imaging (CGIM). Innsbruck, Austria.

[11] Puan, O.C. et al. 2007. Automated Pavement Imaging Program (APIP) for Pavement Cracks Classification and Quantification. Malaysian J. Civ. Eng., 19 (1), p. 1–16.

[12] Tsai, Y. et al. 2010. Critical Assessment of Pavement Distress Segmentation Methods. J. Transp. Eng., 136 (1), p. 11–19.

[13] Salini, R. et al. 2015. Application of artificial intelligence for optimization in pavement management. Int. J. Eng. Technol. Innov., 5 (3), p. 189–197.

[14] Salini, R. 2010. INTELLIPave: Uma Abordagem Baseada em Inteligência Artificial para a Modelagem de Pavimentos Asfálticos. University of Minho.

[15] Salini, R. et al. 2009. INTELLIPave - Considering aside failure criteria and unknown variables in evolutionary intelligence based models for asphalt pavement. In: Proceedings - 23rd European Conference on Modelling and Simulation, ECMS 2009. Madrid, Spain, p. 624–629.

[16] Salini, R. 2004. Salini Method 2004. Comput. Mech. Proc. Sixth World Congr. Comput. Mech. Conjunction with Second Asian-Pacific Congr. Comput. Mech., 2, p. 148–155.

[17] Keys, R.G. 1981. Cubic Convolution Interpolation for Digital Image Processing. Trans. Acoust. Speech, Signal Process., ASSP-29 (6), p. 1153–1160.