Automatic Asphalt Pavement Crack Detection and Classification using Neural Networks

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ABSTRACT: Managing of road maintenance is the most complex task for road administrations. The first presumption for the evaluation analysis and correct road construction rehabilitation is to have accurate and up-to-date information about road pavement condition. As the pavement condition survey is a critical process, it needs fast and cost-effective methods to collect necessary data. The paper proposes a system for automatic road pavement survey that uses image processing techniques to extract features from road images. A Neural Networks approach is used for detection of regions of images with defects and, further processing also, classifying defects into separate types. Proposed system could be used in the future to replace human labour for identification and classification of defects.

1 Introduction

Cracking is one of the most common and important types of asphalt pavement distress. Cracking leads to the deterioration of flexible pavement – stiffness lowering of the asphalt concrete course induces failure in the whole pavement. In addition, cracks in the asphalt surface enable water to infiltrate into base layers and therefore deteriorate their ability to withstand traffic loadings. Generally, cracking distress can be divided into three main types – longitudinal, transversal, and “alligator” cracking (classical fatigue cracking). Examples of different types of cracking are shown on the Figure 1 and Figure 2.

Traditionally, data about pavement cracking has been gathered by human inspectors by collecting data manually through visual surveys. Manual surveys are time consuming and costly and definitely involve a fair amount of subjectivity. There are also dangerous risks to the surveying personnel due to high speeds of public traffic. Rapid achievements of computing technology have given many opportunities for implementation of comprehensive survey of pavement surface distress. Over the last decades, there have been developed many systems for automatic data collection of pavement conditions all over the world [1, 2, 3]. However, completely full-automatic and flexible algorithm for any cases, that could give adequately accurate results for detection and classification of pavement cracking, has been still difficult to achieve. The challenge of the automated data analysis is the extraction and recognition of the features of interest from the images by computer [4].

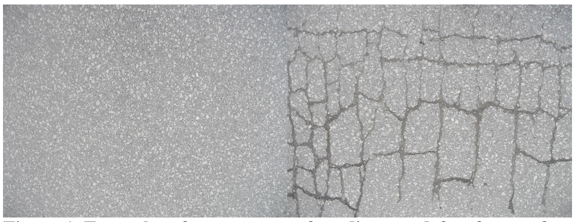

Figure 1. Examples of pavement surface distress: defect free surface (left), alligator cracking (right)

Figure 2. Examples of pavement surface distress: longitudinal cracking (left) and transverse cracking (right)

Generally, the processing of images is divided into three stages: preprocessing, processing and classification. The main characteristic that differentiates automated pavement surface distress inspection systems is the image processing technique used for feature extraction [5]. Principally, the main techniques used for offline image processing are digital filtering, adaptive thresholding, and hierarchical classification.

It has always been a main task for pavement engineers to investigate cracking mechanism. Many researchers [6, 7] have been developed fatigue cracking models for the calculation of pavement service life. Still, there is needed more knowledge about pavement actual performance on the road to predict more accurately pavement cracking as a function of time, loading and environmental conditions. One of the possibilities to improve these models is to analyze the pavement cracking information with data from non-destructive testing devices (e. g. Falling Weight Deflectometer), road surface profilometers and ground penetrating radars. Combining these many used methods for pavement condition assessment in addition to laboratory tests, could promote developing pavement service life prediction models for the design of new and rehabilitation of existing pavements.

2 Previous work

Most of existing methods for detecting defects on pavement surface are based on characteristics of crack. They consider that crack pixels are darker than the ones that surround them. Different authors [1] used fixed threshold to detect dark pixels (cracks). As a key approach of crack detection, thresholding can affect the efficiency of image segmentation during the pre-processing [8].

Another of the methods to extract binary images to be analyzed for detecting pavement distress from initial images is to use an adaptive fuzzy thresholding. The main idea behind this method is based on the fact that crack pixels in pavement images are both continuous and darker than their surroundings [9]. JaChing Chou et al [10] used a fuzzy thresholding technique based on the criterion of maximum fuzzy entropy. They also proposed an approach of applying Hu's, Zernike' and Barnieh' moment invariants and Neural Networks in analyzing pavement images.

Subbirats et al [11] supposed that, by applying a Continuous Wavelet Transform (2D CWT), the differences between crack pixels and background pixels could be brought out. In their approach, crack pixels were identified by thresholding on coefficient maps of 2D CWT through different scales. But in case of "strong texture", the CWT not only brings out crack pixels but also raises noise. Changxia Ma et al [12] proposed an approach of pavement crack detection based on fractional differential and wavelet transform (FDWT) for pavement crack detection. They concluded that image enhancement based on fractional differential is better than these ones based on traditional differential operators.

B. J. Lee et al [13] studied three spatial neural networks in order to classify various crack types according to digital pavement images: 1) image-based neural network, 2) histogram-based neural network and 3) proximity-based neural network. Guoai Xu [14] used back-propagating neural networks for extracted features to classify different crack types. For pre-processing they used set of histogram equalization, spatial filtering, and binary processing.

Rababaah et al [15] compared projection and Hough feature extraction methods. They also compared genetic algorithm, self organizing map and multilayer perception classification methods. Oliveira et al [16] and Yaxiong Huang [17] proposed an approach in which, they divide an image into grid cells and after doing that each cell is classified as crack or crack-free cell by using the mean and variance of the grayscale values.

It has been showed that Falling Weight Deflectometers (FWD) are useful tools to evaluate cracking in asphalt layers. Insoo Yeo et al [6] used a portable FWD to estimate the modulus of the asphalt layer after a number of loadings were applied. Jianjun Yin et al [18] studied the seriousness of earthquake induced cracks in airport asphalt pavements.

3 Method

In order to effectively detect and classify cracks on the pavement, the picture has to go through three processing stages: pre-processing, processing and classification. Pre-processing is used to equalize intensity values across picture. Processing stage is used to extract features for neural network (NN). NN is applied for crack detection and classification. Input of proposed system is picture of the pavement and output is a number representing one of the four states. These states are: 1 – no defect 2 – transverse crack 3 – longitudinal crack and 4 – alligator crack.

Pictures were taken during daylight about 1.2 m from ground level. Dimensions of the original pictures were 3648x2736 pixels. It was tried to avoid direct bright sunlight because very bright light complicates substantially detection of darker cracked areas. Nevertheless, colour and lighting conditions of pavements varied greatly. Pictures taken from different pavement types were used. Ages of pavements were approximately between 5-10 years. Pictures for testing were chosen randomly. Processing and classification was made on PC using SCILAB and MATLAB software.

1) Pre-Processing

Firstly colour images have to be converted to greyscale. Lens properties and uneven lighting can cause uneven intensity values across the picture. Cracks in the centre of the picture can have different intensity values from the cracks near the edges of the picture. To level out these differences, equalization has to be used across the picture. Original picture will be divided into 96x96 pixel size sub-matrices. Maximum value of this sub-matrix will be compared to overall maximum value. Intensity values inside sub matrix will then be corrected by multiplying them with the coefficient. Due to pre-processing stage pictures manual thresholding will not be used. This makes proposed system more adaptive and less labour costly.

2) Processing

For faster processing original image is divided in to 12x12 pixel size sub-matrices. This size covers approximately a typical width of a pavement cracks. New binary matrix is formed by comparing sub-matrices mean value to original matrix mean value. If sub-matrix mean value is lower, then one can assume that inside that area is a defect. If the mean value is higher, then this 12x12 pixel area probably contains no defects. Boolean matrix represents probable areas with and without defects (1 – probable cracked area; 0 – area without defects. By adding all probable defect areas (all the ones in Boolean matrix) we get first neural network input parameter.

Next matrix is summed column- and row-wise. As a result, two vectors are calculated, one parallel to x and other to y axis. Lengths of these vectors are equal to binary matrix height and width. Median and maximum values of these vectors are used as second and third NN input parameters.

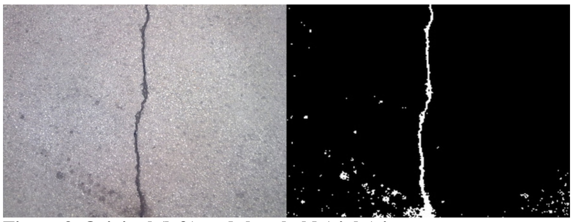

Figure 3. Original (left) and threshold (right) image

Median and maximum values of these matrices are used for NN input. Maximum values indicate the lengths of the cracks and the median values indicate overall number of smaller defects. Pictures with longitudinal or transversal crack have high projection vector maximum value and low median value. Pictures with alligator cracks have high median value of the projection vectors.

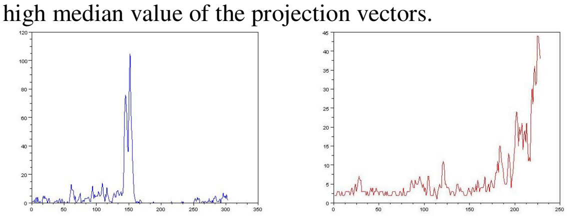

Figure 4. Projection vectors, x-axis (left) and y-axis (right)

For better noise suppression, binary matrix is convolved with two 11x11 pixel size convolution masks. One of the convolution masks has a vertical and the other one horizontal line in the middle. By convolving with these masks all vertical or horizontal lines respectively, will be preserved. While using these masks, small regions of noise will be suppressed. These areas can be caused by sensor-noise or bright reflections from pavement. As a result two new matrices will be formed. Two resulted matrices are summed to get two last NN input parameters. By using convolution, the system ability to detect transversal and longitudinal cracks is improved.

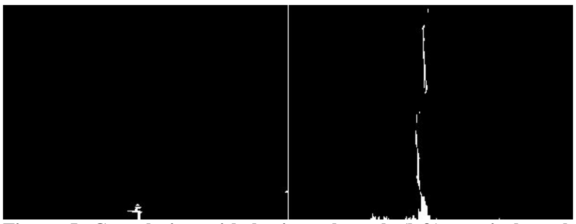

Figure 5. Convolution with horizontal mask (left), vertical mask (right) of image containing longitudinal crack

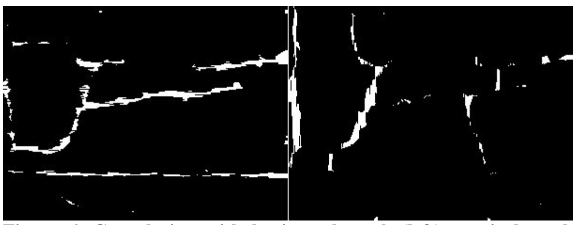

Figure 6. Convolution with horizontal mask (left), vertical mask (right) of image containing alligator crack

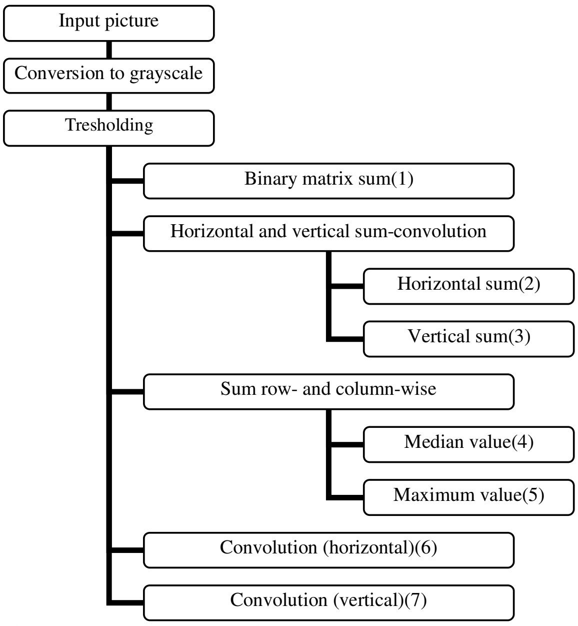

Figure 7. Processing scheme with 7 parameters

3) Classification

To detect and classify cracks, Neural Network was being used. NN had 7 input and 4 output nodes. Network consisted of 21 hidden layers. Four output nodes indicate the following states: 1 – no crack, 2 – transverse crack, 3 – longitudinal crack, 4 – alligator crack. Collected samples (pictures) were separated into three different groups: training, validating and data testing. Overall 61 pictures were used to train network, 41 to validate and 41 to test the network.

4 Results

Proposed system could effectively identify and classify defects with relatively good results. In 98 per cent of the cases, the system was able to effectively detect crack on an image. In 95 per cent of the cases classification was correct. Overall accuracy of the system was 89.3 per cent when crack detection and classification were combined. MSE of test data was 0.4 and regression error value was 0.98. Alligator crack classification showed poorest results (Table 1). 12 per cent of the alligator crack images were classified as longitudinal or transversal cracking. This could be caused due to thin cracks which the system was unable to detect. It can be said that thin cracks on the noisy images are often removed as noise Better results could be achieved if training dataset would be larger.

Crack type	Correctly detected images (%)
Longitudinal	96
Transversal	96.6
Alligator	84

Table 1. Classification results

5 Future work

Improving of the system by increasing the training dataset is going to be done for the next step. With doing that it could be possible to raise the system ability to detect complicated alligator cracking.

Secondly, a short field test project will going to be carried out using together the prototype of proposed system and FWD measurements. The aim of that is to investigate the cracking potential by structural condition indicators of the pavement, such as FWD deflection basin parameters, and detection of visual cracking on the road surface.

6 Conclusions

In this paper a novel approach for automatic pavement crack detection and classification has been proposed. The system uses Neural Network for both to detect and classify the pavement defects. In the main processing stage convolution masks are used.

Proposed measurement system and results of the analysis showed a great potential for using the system as an automatic road pavement survey instrument. In the future, more developed system could be used by road engineers as an everyday tool for a road condition monitoring.

7 Acknowledgements

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References

[1] T. S. Nguyen, M. Avila, B. Stepahane, “Automatic detection and classification of defect on road pavement using anisotropy measure”. 17th European Signal Processing Conference (Glasgow, Scotland, August 24-28), 2009

[2] A. Mraz, M. Gunaratne, A. Nacef, and B. Choubane, “Experimental Evaluation of a Pavement Imaging System, Florida Department of Transportation’s Multipurpose Survey Vehicle”. Journal of the Transportation Research Board, No. 1974, TRB, Washington, D.C., pp. 97-106, 2006

[3] T. Lovas, I. Kertesz, I. Fi, and A. Barsi, “Photogrammetric pavement detection system”. Pavement Cracking – Al-Qadi, Scarpas & Loizos, Taylor & Francis Group, London, pp. 873-879, 2008.

[4] K. C. P. Wang, W. Gong, and Z. Hou, “Automated cracking survey”. Pavement Cracking – Al-Qadi, Scarpas & Loizos, Taylor & Francis Group, London, pp. 881-896, 2008.

[5] Yaxiong Huang and Bugao Xu, “Automatic inspection of pavement cracking distress”. Journal of Electronic Imaging, vol. 15(1), 2006

[6] Insoo Yeo, Youngchan Suh, Sungho Mun, “Development of a Remaining Fatigue Life Model for Asphalt Black Base trough Accelerated Pavement Testing”. Construction and Building Materials 22, pp. 1881-1886, 2008.

[7] Dong-Yeob Park, Neeraj Buch, and Young-Chan Suh, “Development of Fatigue Cracking Prediction Model for Flexible Pavements”. KSCE Journal of Civil Engineering, Vol. 5, No. 4, pp. 397-402, 2001.

[8] Wei Wei, Boying Liu, Peng Bai, “Automatic Road Crack Image Preprocessing for Detection and Identification”. IEEE, 978-0-7695-3852-5/09, 2009.

[9] Fanfan Liu, Guoai Xu, Yixian Yang, Xinxin Niu, Yuli Pan, “Novel Approach to Pavement Cracking Automatic Detection Based on Segment Extending”. IEEE, 978-0-7695-3488-6/08, 2008.

[10] JaChing Chou, Wende A. O’Neill, H.D. Cheng, “Pavement Distress Classification Using Neural Networks”. IEEE, 0-7803-2129-4/94, 1994.

[11] P. Subbirats, J. Dumoulin, V. Legeay, and D. Barba, “Automation of Pavement Surface Crack Detection using the Continous Wavelet Transform”, IEEE, 1-4244-0481-9/06, 2006.

[12] Changxia Ma, Wengming Wang, Chuanxia Zhao, Feng Di, Zhengli Zhu, “Pavement Cracks Detection Based on FDWT”, IEEE, 978-4244-4507-3/09, 2009.

[13] B. J. Lee and H. D. Lee, “A Robust Position Invariant Artificial Neural Network for Digital Pavement Crack Analysis”. TRB Annual Meeting, 2003

[14] Guoai Xu, Jianli Ma, Fanfan Liu, Xinxin Niu, „Automatic Recognition of Pavement Surface Crack Based on BP Neural Network”, IEEE, 978-0-7695-3504-3/08, 2008.

[15] H. Rababaah, D. Vrajitoru, J. Wolfer, „Asphalt Pavement Crack Classification: A Comparison of GA, MLP, and SOM”, Proceeding of The Genetic and Evolutionary Computation Conference (GECCO'05 and SIGEVO 1), Washington, DC, June25-29, 2005

[16] H. Oliveira and P. L. Correia, “Identifying and retrieving distress images from road pavement surveys”. IEEE 978-1-4244-1764-3/08 2008 IEEE A. Author, M. Stern, and R. Smith, "Title of the paper". Electronics Letters, vol. 28, No. 11, pp. 1180-1182, 1995.

[17] Yaxiong Huang, Bugao Xu, “Automatic Inspection of Pavement Cracking Distress”, Journal of Electronic Imaging 15(1), 013017, 2006.

[18] Jianjun Yin, Yoshitaka Hachiya, and Takeshi Nakamura, “Structural Evaluation for Airport Asphalt Pavements with Earthquake Induced Cracks”. JSCE, Journal of Pavement Engineering, Vol. 2. pp 81-88, 1997.