JOURNAL OF TRAFFIC AND TRANSPORTATION ENGINEERING (ENGLISH EDITION) 2015; 2 (6): 391–398

HOSTED BY

ELSEVIER

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/jtte

Original Research Paper

Network level pavement evaluation with 1 mm 3D survey system

Kelvin C. P. Wang [a,*], *Qiang Joshua Li* [a], *Guangwei Yang* [a], *You Zhan* [a], *Yanjun Qiu* [b]

[a] *School of Civil and Environmental Engineering, Oklahoma State University, Stillwater, OK 74078, USA*

[b] *School of Civil Engineering, Southwest Jiaotong University, Chengdu 610031, China*

ARTICLE INFO

Article history:

Available online 20 October 2015

Keywords:

PaveVision3D Ultra

Rapid network survey

Pavement surface evaluation

Dynamic segmentation

ABSTRACT

The latest iteration of PaveVision3D Ultra can obtain true 1 mm resolution 3D data at full-lane coverage in all 3 directions at highway speed up to 60 mph. This paper introduces the PaveVision3D Ultra technology for rapid network level pavement survey on approximately 1280 center miles of Oklahoma interstate highways. With sophisticated automated distress analyzer (ADA) software interface, the collected 1 mm 3D data provide Oklahoma Department of Transportation (ODOT) with comprehensive solutions for automated evaluation of pavement surface including longitudinal profile for roughness, transverse profile for rutting, predicted hydroplaning speed for safety analysis, and cracking and various surface defects for distresses. The pruned exact linear time (PELT) method, an optimal partitioning algorithm, is implemented to identify change points and dynamically determine homogeneous segments so as to assist ODOT effectively using the available 1 mm 3D pavement surface condition data for decision-making. The application of 1 mm 3D laser imaging technology for network survey is unprecedented. This innovative technology allows highway agencies to access its options in using the 1 mm 3D system for its design and management purposes, particularly to meet the data needs for pavement management system (PMS), pavement ME design and highway performance monitoring system (HPMS).

1. Introduction

Accurate and timely information on pavement surface characteristics is critical for evaluating the performance, condition, and safety of pavement infrastructure. Both pavement design and management rely on these and other information for comprehensive pavement evaluation. Pavement data collection technologies have been improved gradually in the last few decades. However, due to sensor and computing limitations, limited research funding, and inherent difficulties to meet stringent requirements of precision and bias, to

* *Corresponding author*. Tel.: +1 405 744 5206; fax: +1 405 744 7554.

E-mail addresses: kelvin.wang@okstate.edu (K. C. P. Wang), qiang.li@okstate.edu (Q. J. Li), guangwy@okstate.edu (G. Yang), jason.zhan@okstate.edu (Y. Zhan), publicqiu@vip.163.com (Y. Qiu).

Peer review under responsibility of Periodical Offices of Chang'an University.

http://dx.doi.org/10.1016/j.jtte.2015.10.005

automatically obtain pavement cracking and other distress data have not been realized by the necessary hardware and software. In addition, roughness, rutting, and macro-texture data are currently obtained through separated instrumentation on a relatively small area within a pavement lane.

Pavement engineering as an area of study has suffered from inadequate and poor quality distress data. High quality pavement distress data for the next-generation pavement design system, pavement ME design (DARWin-ME), is critically needed to facilitate the calibration of prediction models and further validation of relevant mechanistic models. Further, many state highway agencies have collected pavement distress data, particularly cracking data, for years through manual, automated, or semi-automated means. However, such data sets are of poor quality due to problems associated with consistency, repeatability, and accuracy of collected data and subsequent analyses. In addition to being slow and unsafe when conducted in the field, manual survey results show wide variability (Wang, 2004). Automation technology for pavement survey has long been sought and tested for precision and bias (McGhee, 2004; Wang et al., 2011; Wang, 2011). The early operating system is based on 1 mm 2D laser images of pavement surface, which poses challenges in terms of further improving its accuracy and consistency. Cracks, along with many other pavement surface defects, all have their own unique and distinctive characteristics in the 3rd dimension, which are lost in 2D images. Therefore, developing a new technology that can capture realistic pavement surface characteristics in the digital domain at sufficiently high resolution, or actual surface models of pavements, is a necessary task.

Recently, the research team at Oklahoma State University has developed and implemented 3D laser imaging based sensors for pavement condition survey. With the latest PaveVision3D Ultra (3D Ultra for short), the resolution of surface texture data in vertical direction is about 0.3 mm and in the longitudinal direction is approximately 1 mm at data collection speed of 60 mph. All pavement surface data gathered at this speed, and 1 mm resolution would provide engineers advantages in both visualization and analysis.

This paper introduces the 3D Ultra technology for rapid network level pavement survey on Oklahoma interstate highways. The collected 1 mm 3D data are automatically analyzed with comprehensive solutions for automated evaluation of pavement surface including longitudinal profile for roughness, transverse profile for rutting, predicted hydroplaning speed for safety analysis, and cracking and various surface defects for distresses. The pruned exact linear time (PELT) method, an optimal partitioning algorithm, is implemented to identify change points and dynamically determine homogeneous segments to assist DOTs effectively through using the available 1 mm 3D pavement surface condition data for decision-making.

2. 3D Ultra data acquisition system

2.1. Overview

The PaveVision3D laser imaging system has been evolved into a sophisticated system to conduct full lane data collection on roadways at highway speed up to 60 mph (about 100 km/h) at 1 mm resolution (Wang, 2011). Fig. 1 demonstrates the digital highway data vehicle (DHDV) equipped with 3D Ultra. 3D Ultra is able to acquire both 3D laser imaging intensity and range data from pavement surface through 2 separate sets of sensors. Recently, two 3D high resolution digital accelerometers have been installed on the system, which are capable of reporting compensated pavement surface profile and generating roughness indices. The collected data are saved by image frames with the dimension of 2048 mm in length and 4096 mm in width. In summary, the 1 mm 3D pavement surface data can be used for.

Fig. 1 – DHDV with 3D Ultra (WayLink).

(1) Comprehensive evaluation of surface distresses: automatic and interactive cracking detection and classification based on various cracking protocols;
(2) Profiling: transverse for rutting and longitudinal for roughness (Boeing Bump Index and International Roughness Index);
(3) Safety analysis: macro-texture assessment in term of mean profile depth (MPD) and mean texture depth (MTD), hydroplaning prediction, and grooving identification and evaluation;
(4) Roadway geometry survey: horizontal curve, longitudinal grade and cross slope.

2.2. Hardware system

With the high power line laser projection system and custom optic filters (Fig. 2), DHDV can work at highway speed during daytime and nighttime ensuring image quality and consistency. As the latest imaging sensor technology, 3D Ultra is able to acquire both intensity and range laser imaging data from pavement surface through 2 separate sensors. In addition to the 3D camera sensors, the

Fig. 2 – Laser imaging principle (WayLink).

positioning data collections (including precision gyro, high-frequency differential GPS receiver, distance measurement instrument, and inertial measurement unit (IMU)) are incorporated into the 3D Ultra to ensure high geographic accuracy. An IMU is an electronic device that measures and reports the velocity, orientation, and gravitational forces using a combination of accelerometers and gyroscopes. An IMU allows a GPS to work when GPS-signals are unavailable, such as in tunnels, inside buildings, or under electronic interference. IMUs work, in part, by detecting orientational changes in pitch, roll, and yaw, and can be used to determine pavement geometric parameters such as horizontal curves, longitudinal grade, and cross slope.

2.3. *Software system*

The 3D Ultra system installs 2 key software applications, the 3D automated distress analyzer (ADA3D) (Fig. 3) and the multimedia based highway information system (MHIS) (Fig. 4). ADA3D is an automatic cracking analyzing tool. By implanting the sophisticated algorithms, ADA3D is currently capable of conducting automated cracking, rutting, roughness, and texture analyses with 1 mm resolution at highway speed based on several cracking protocols. ADA3D also allows users to perform semi-automated distress analysis.

3. Network level data collection

The data were collected from Oklahoma interstate network I-35 and I-40, and State Highway 51 from I-35 to Sand Springs with a total of approximately 1280 center miles, as shown in Fig. 5 in bold red. Since all the highways are divided, the data for both directions are collected. The 2 separate data collection trips at highway speed were done to acquire 1 mm 3D data using the PaveVision3D system.

The collected data are analyzed by ADA3D. The following surface characteristics are reported.

(1) IRI values in the left and right wheel path at every 0.1 miles;
(2) Rut depth in the left and right wheel path at every 0.1 miles, the rut depth is calculated based on the first profile of each 0.1 miles section;
(3) Cracking data in the wheel path and non-wheel path zones at every 0.1 miles, cracking data are obtained based on the AASHTO (2013b);
(4) Predicted hydroplaning speed at every 0.1 miles.

4. Network level pavement evaluation

4.1. *PELT based dynamic segmentation*

Segmenting pavement network into homogenous sections is important for road maintenance scheduling and management systems. The 3 types of segmentation approaches are used by highway agencies: fixed-length segments, variable-length segments, and dynamic segmentation. Fixed-length static method breaks highway routes into pre-defined lengths (such as every 0.1 miles). Since it is insensitive to changes of pavement attributes, it may result in significant data redundancy and problems to provide recommendations for project prioritization (Thomas, 2003). Variable-length static method, on the other hand, can break pavement into any length, but may be too sensitive to attribute changes and result in a large number of fine segments within a highway network (Thomas, 2003). Dynamic segmentation (DS) can accommodate the integration of both fixed and variable-length methods, and provide more flexible data management.

In this paper, the newly developed PELT method (Killick et al., 2012) is implemented to dynamically segment pavement sections into uniform subsections by using 1 mm 3D pavement surface data. The PELT algorithm conducts an exact search, and is considered much more computationally efficient by removing solution paths that are not known to lead to optimality (called as "prune" process). Assuming an ordered sequence of data $y_{1:n} = (y_1, \cdots, y_n)$, has m change points with their positions at $\tau=(\tau_1, \cdots, \tau_m)$. Consequently the m change points split the data into $m+1$ segments, with the i-th segment containing $y_{(\tau_{i-1}+1):\tau_i}$, the objective to

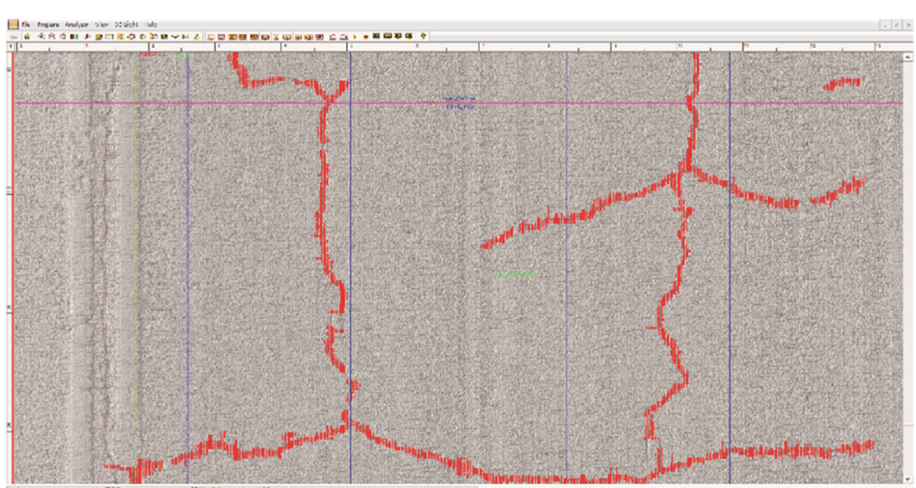

Fig. 3 – Operating interface of ADA3D.

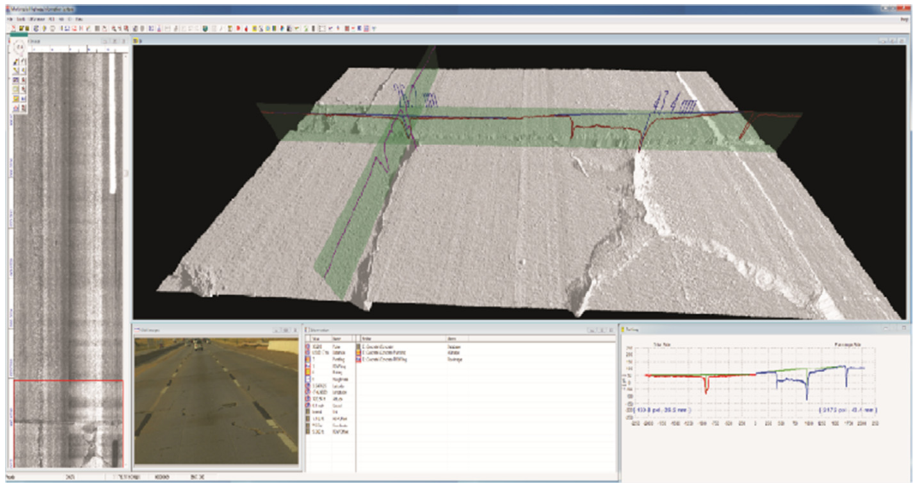

Fig. 4 – MHIS-3D interface.

identify multiple change points can be formulated to minimize as (Killick et al., 2012)

$$\sum_{i=1}^{m+1}\left[C\left(y_{(\tau_{i-1}+1):\tau_i}\right)\right]+\beta_f(m) \tag{1}$$

where $C(\cdot)$ is the cost function, $\beta_f(m)$ is the penalty to guard against over fitting. The PELT method considers the data sequentially and searches the solution space exhaustively. The high computational efficiency is achieved by removing solution paths that are not known to lead to optimality. The assumptions and theorems, which allow removal of solution paths, are explained further by Killick et al. (2012). Pseudo-code for the PELT method is given in Table 1 (Killick et al., 2012).

4.2. *International roughness index (IRI)*

The 2 high accuracy digital accelerometers are mounted inside the 3D Ultra sensors to provide the inertial reference information. The measured pavement longitudinal road profiles are obtained by combining the height information with the inertial reference data. Filtering algorithms are applied to remove unwanted data for IRI calculation. IRI values in the left and right wheel paths, and the average IRI are calculated in inches per mile for each image frame, and summarized for each 0.1 miles pavement segment. PELT change points are determined for each highway section. Assuming IRI values of 95, 170 inch/mile are the thresholds to classify pavement into "good", "moderate", and "poor" conditions, most majority of

Fig. 5 – Highway network survey for ODOT.

Table 1 – Pseudo-code for the PELT method.

Input	A time series of the form, $(y_1, y_2, \cdots, y_n)$, where $y_i \in R$.
	A measure of fit $C(\cdot)$ dependent on the data.
	A penalty β which does not depend on the number or location of change points.
	A constant K that satisfies equation.
Initialize	Let n = length of time series and set $F(0) = -\beta$, $C_p(0) = 0$, $R_1 = \{0\}$
Iterate	For $\tau^* = 1, \cdots, n$
	(1) Calculate $F(\tau^*) = \min_{\tau \in R_{\tau^*}} [F(\tau) + C(y_{(\tau+1):\tau^*}) + \beta]$
	(2) Let $\tau^1 = \arg\min_{\tau \in R_{\tau^*}} [F(\tau) + C(y_{(\tau+1):\tau^*}) + \beta]$
	(3) Set $C_P(\tau^*) = [C_P(\tau^1), \tau^1]$
	(4) Set $R_{\tau^*+1} = \{\tau \in R_{\tau^*} \cup \{\tau^*\} : F(\tau) + C(y_{(\tau+1):\tau^*}) + K \le F(\tau^*)\}$
Output	The change points recorded in $C_p(n)$.

the highways are in "good" and "moderate" conditions. I-35 North Bound in the left wheel path as the example is shown in Fig. 6, it can be seen that only 1.17% of the pavement are segmented as "poor" roughness condition with IRI values greater than 170 inch/mile, 18.66% as "moderate" condition with IRI between 95 and 170 inch/mile, while the rest 80.17% have IRI values lower than 95 inch/mile.

4.3. *Rutting*

Rutting is defined as the permanent traffic-associated deformation within pavement layers. The recently provisional approved AASHTO (2013a) has been implemented into the 3D Ultra system for rutting characterization and cross slope measurements. Rutting in the left and right wheel paths and the average are calculated in inches for each image frame and summarized for each 0.1 miles pavement segment. Assuming rutting depths of 0.25 inches and 0.75 inches are the thresholds to classify pavement into "good", "moderate", and "poor" rutting conditions, and most majority of the highways have rutting less than 0.25 inches (as shown in Fig. 7), which are classified as "good" condition.

4.4. *Alligator cracking*

The AASHTO (2013b) outlines the procedures for quantifying cracking distress at network level. In this designation, measurements and reports of the 30 cracking related values have considered 3 cracking types (longitudinal, transverse, and pattern cracking), 2 attributes (cracking length and cracking width), and 5 traffic zones (3 in non-wheel path and 2 in wheel path).

In order to produce manageable results, only fatigue cracking is investigated in this paper, which is estimated from pattern cracking derived from AASHTO (2013b), resulting in both wheel paths and reported as the percentage of the wheel path areas. Fatigue cracking in the left and right wheel paths is calculated for each 0.1 miles pavement segment. As shown in Fig. 8, PELT change points are determined for each section. The figures provide decision

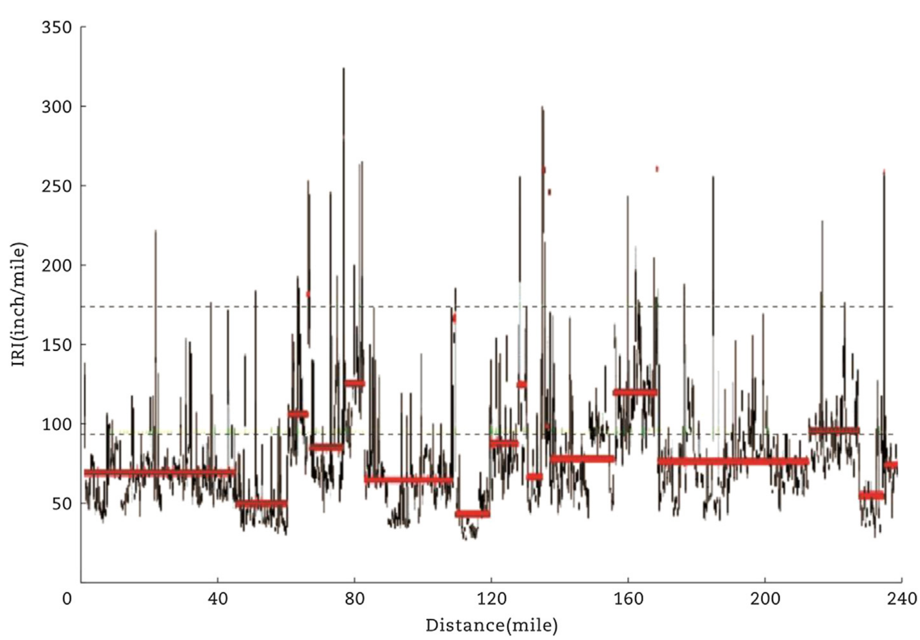

Fig. 6 – IRI and PELT segmentation results for I-35 north bound.

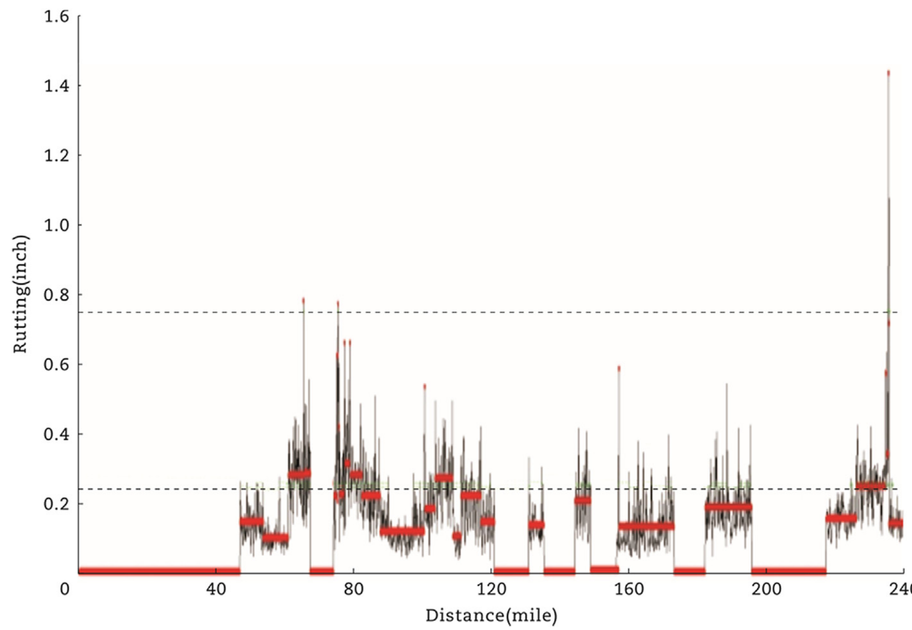

Fig. 7 – Rutting values and PELT segmentation results for I-35 north bound.

makers with visuals where cracks have occurred. Assuming fatigue cracking of 5% and 25% of the wheel path areas are the thresholds to classify pavement into "good", "moderate", and "poor" cracking conditions, most majority of the highways have fatigue cracking less than 5%, which are classified as "good" cracking condition.

4.5. *Hydroplaning speed*

During high intensity rainfall events, hydroplaning will likely occur and affect driving safety. Hydroplaning is dependent on surface texture properties, flow path slope, flow path length, rainfall intensity, and pavement surface type. PAVDRN model has been widely used to estimate the hydroplaning speed (HPS) (Anderson et al., 1998). It uses a one-dimensional steady state form of the kinematic wave equation (Eq. (2)) to calculate the water film depth (WFD). The flow path length and flow path slope can be obtained by Eqs. (3) and (4). The program also uses a condensation of formulas (Eqs. (5) and (6)) to determine the relationship between velocity at which hydroplaning initiates and WFD (Anderson et al., 1998).

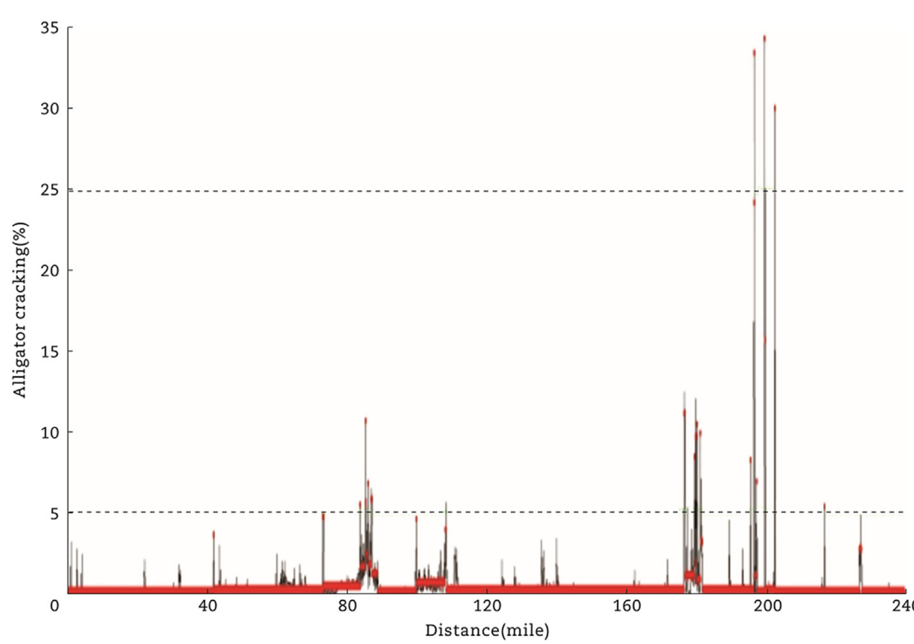

Fig. 8 – Alligator cracking and PELT segmentation results for I-35 north bound.

$$\mathrm{WFD} = \left(\frac{nL_f I}{36.1 S_f^{0.5}}\right)^{0.6} - \mathrm{MTD} \tag{2}$$

$$S_f = \left(S_l^2 + S_c^2\right)^{\frac{1}{2}} \tag{3}$$

$$L_f = W\frac{S_f}{S_c} \tag{4}$$

$$\mathrm{HPS} = 26.04\mathrm{WFD}^{-0.259} \quad \mathrm{WFD} < 0.095 \text{ inch or } 2.4 \text{ mm} \tag{5}$$

$$\mathrm{HPS} = 3.09A \quad \mathrm{WFD} \geq 0.095 \text{ inch or } 2.4 \text{ mm} \tag{6}$$

where MTD is mean texture depth(inch), L_f is flow path length(inch), S_f is flow path slope, S_l is longitudinal grade, S_c is cross slope, I is excess rainfall rate(inch/hr), n is Manning's roughness coefficient, W is pavement drainage width (foot), A is the greater value calculated using

$$A = \max\left\{\frac{10.409}{\mathrm{WFD}^{0.06}} + 3.57, \left(\frac{28.952}{\mathrm{WFD}^{0.06}} - 7.817\right)\mathrm{MTD}^{0.14}\right\} \tag{7}$$

In this study, the MTD is substituted by estimated MTD (EMTD) derived from the simulated sand patch based volumetric measuring method using 1 mm 3D surface data continuously collected at highway speed (Luo et al., 2014). Cross slope and longitudinal grade data are acquired with an IMU system. The rainfall precipitation data are obtained from NOAA'S National Water Service (2014).

Predicted hydroplaning speeds are calculated for each 0.1 miles pavement segment. Moderate rain intensity is used for hydroplaning prediction. As shown in Fig. 9, PELT change points are determined for each section. Assuming predicted hydroplaning speed 5 mph higher and 15 mph lower than the posting speed limits are the thresholds to classify pavement safety into "good", "moderate", and "poor" hydroplaning conditions, most majority of the highways have predicted hydroplaning speeds between 55 and 75 mph, which are classified as "moderate" conditions. In case of moderate rain, driving at posted or higher speed will be subjected to hydroplaning for most majority of the highways. Based on the prediction results, several segments have predicted hydroplaning speeds lower than 60 mph.

4.6. Discussions

Even though the interstate highways under study are considered to be in "good" condition for most majority of pavement surfaces according to IRI, rutting, and estimated fatigue cracking, significant amount of pavement segments is in "moderate" conditions based on predicted hydroplaning speed. In other words, no roughness, rutting, and cracking issues are found on most pavement, while hydroplaning related safety hazards are presented for many pavement locations if users drive at posted or higher speeds during moderate rain. The dynamic segmentation results can assist DOT decision makers to identify the locations where issues may be presented, evaluate pavement performance in a comprehensive manner from various perspectives, and assist project prioritization and maintenance scheduling.

5. Conclusions

Using PaveVision3D Ultra technology, rapid pavement survey is conducted at highway speed to collect geographically true and complete pavement surfaces or virtual pavement surfaces with inertial measurement unit (IMU) at 1 mm resolution for approximately 1280 lane miles of interstate highways in Oklahoma. With sophisticated ADA software interface, the collected 1 mm 3D data can provide highway agencies with automated evaluation of pavement surface including cracking, rutting, roughness, and hydroplaning speed for safety analysis. The pruned exact linear time (PELT) method is implemented to identify change points and dynamically

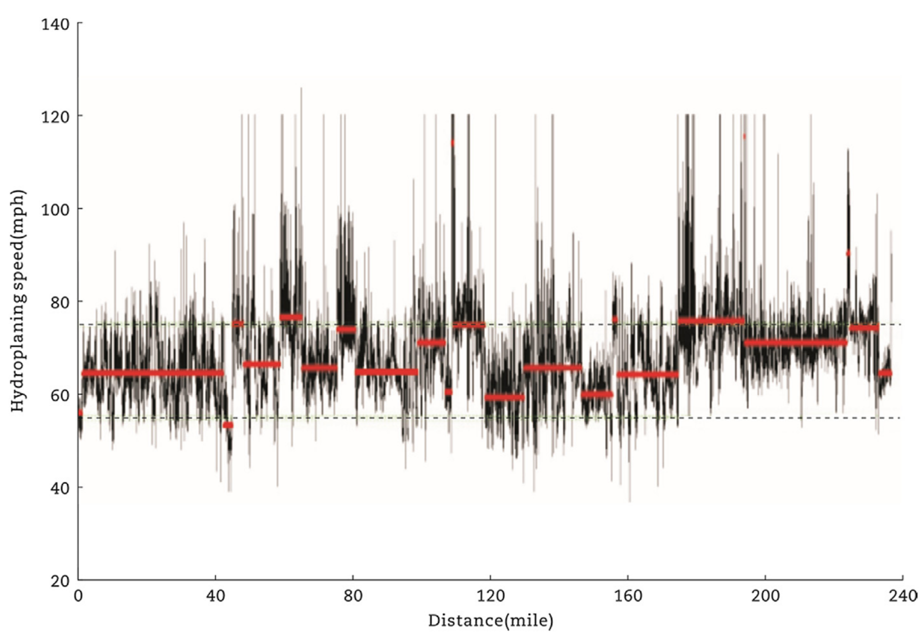

Fig. 9 – Hydroplaning speeds and PELT segmentation results for I-35 north bound.

determine homogeneous segments so as to assist Oklahoma Department of Transportation (ODOT) effectively using the available 1 mm 3D pavement surface condition data for decision-making. This innovative technology allows highway agencies to access its options in using the 1 mm 3D system for pavement design and management purposes, particularly to meet the data needs for pavement management system (PMS), pavement ME design and highway performance monitoring system (HPMS).

Acknowledgments

This work was partially sponsored by the Oklahoma Department of Transportation (ODOT).

REFERENCES

American Association of State Highway and Transportation Officials (AASHTO), 2013a. Standard Practice for Determining Pavement Deformation Parameters and Cross Slope from Collected Transverse Profiles, AASHTO Designation PP69–10. AASHTO, Washington DC.

American Association of State Highway and Transportation Officials (AASHTO), 2013b. Quantifying Cracks in Asphalt Pavement Surfaces from Collected Images Utilizing Automated Methods, AASHTO Designation PP67–10. AASHTO, Washington DC.

Anderson, D.A., Huebner, R.S., Reed, J.R., et al., 1998. Improved surface drainage of pavements. In: NCHRP Web Document, Washington DC, 1999.

Killick, R., Fearnhead, P., Eckley, I.A., 2012. Optimal detection of changepoints with a linear computational cost. Journal of the American Statistical Association 107 (500), 1590–1598.

Luo, W., Wang, K.C.P., Li, L., et al., 2014. Surface drainage evaluation for rigid pavements using an inertial measurement unit and 1-mm three-dimensional texture data. Journal of the Transportation Research Board 2457, 121–128.

McGhee, K.H., 2004. Automated Pavement Distress Collection Techniques: A Synthesis of Highway Practice. NCHRP Synthesis 334. Transportation Research Board, Washington DC.

Precipitation Frequency Data Server (PFDS). Available at: http://dipper.nws.noaa.gov/hdsc/pfds/index.html (Date accessed: July 2014).

Thomas, F., 2003. Statistical approach to road segmentation. Journal of Transportation Engineering 129 (3), 300–308.

Wang, K.C.P., 2004. Automated pavement distress survey through stereovision. In: NCHRP-IDEA Program Project Final Report, Washington DC.

Wang, K.C.P., Gong, W., Tracy, T., et al., 2011. Automated Survey of Pavement Distress Based on 2D and 3D Laser Images. MBTC DOT 3023. Mack-Blackwell Rural Transportation Center, Fayetteville.

Wang, K.C.P., 2011. Elements of automated survey of pavements and a 3D methodology. Journal of Modern Transportation 19 (1), 51–57.