Challenges and Lessons from the Successful Implementation of Automated Road Condition Surveys on a Large Highway System

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***Abstract*— Signal processing based automated road condition surveys (ARCS) system are the solution for the current unsafe, subjective and labor-intensive manual road condition surveys. Although extensive research has been conducted on methods for ARCS, application by transportation agencies is still minimal. In 2016, an ARCS system, developed by Georgia Tech, was successfully implemented on a 4,184km highway system in Georgia, USA. This paper presents the insights gained from the project and also discusses the remaining challenges with a focus on crack detection and classification. Crack fundamental elements were implemented to obtain a flexible multi-scale output. A combination of ARCS and QA/QC tools were used to obtain high accuracy results while minimizing human effort. Gaps in ARCS research, such as the lack of a crack detection algorithm performance measure were revealed. The solutions and new challenges revealed from this study will help ARCS researchers to create solutions which can be readily applied by transportation agencies.**

I. INTRODUCTION

In 2015, the US Federal Highway Trust Fund spent USD 42.95 Billion [1] out of which the principal expenditure was maintenance of existing highway infrastructure. Regular road infrastructure condition surveys are required for optimized infrastructure asset management. Several transportation agencies still conduct manual surveys in which data collection and processing is done simultaneously and manually. Semi-automated surveys have also become common, in which the road data is collected using vehicle-mounted sensors and processed manually later.

On-foot portions of manual surveys create a safety concern. Semi-automated surveys can eliminate the safety concern but the data still has to be manually processed. Hence, manual and semi-automated approaches are expensive, time-consuming and laborious. The next subsection describes a specific example of a manual survey approach in detail.

A. Current Practice in Georgia

In the US state of Georgia, the Georgia Department of Transportation (GDOT) conducts road infrastructure condition surveys annually. Specific protocols have been published to guide the survey effort for different types of assets. For example, the Computerized Pavement Condition Evaluation System (COPACES) protocol [2] is followed for evaluating asphalt pavements.

The COPACES protocol requires a windshield survey of the pavement condition, in which the road condition is assessed by a passenger in a vehicle moving at highway speeds. Additionally, a representative 30.5m (100 feet) section of roadway has to be identified in every 1.6km (1 mile), on which measurements have to be taken on foot. Moving traffic barrier vehicles are used to provide protection at the cost of mobility. Georgia has over 4,184 centerline kilometers of interstates alone. After the surveys are completed, the survey data has to be processed and aggregated to obtain project ratings (scores from 0 to 100 to quantify asset condition) which are used to guide maintenance, rehabilitation and repair (MR&R) decisions.

B. Automated Road Condition Surveys

Automated Road Condition Survey (ARCS) systems provide a safe and efficient alternative to the manual and semi-automated road condition survey procedures. ARCS systems consist of data collection using vehicle-mounted sensors and data processing using automated infrastructure condition detection and classification algorithms. In US federal protocols [3] as well as state protocols [2], [4], road pavement condition is generally evaluated by measuring the extent and severity of distresses on the roadway pavement, such as cracking, rutting and potholes. Extensive research has been conducted to develop methods for the detection and classification of these pavement distresses, based on signals (e.g. 2D images and 3D pavement data) captured from vehicle-mounted sensors. However, ARCS is not widely used by transportation agencies. One reason is that existing ARCS products may not deliver the final protocol requirements and further processing is required. Accuracy is also a problem. For example, crack detection algorithms may not perform well in all the pavement scenarios encountered in the field. Hence, there is a gap between ARCS research and the needs of transportation agencies, which is the focus of this paper.

This paper uses the successful implementation of an ARCS system in 2016 for the Georgia interstate system to gain insights and understand the challenges restricting the widespread adoption of ARCS. This paper focuses on signal processing based approaches to ARCS, which is the most common approach.

This section explained the background, research need and objective of this paper. The next section provides an overview of the ARCS system implemented for the Georgia interstate system. This is followed by the observations on

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Fig. 1. The Georgia Tech Survey Vehicle (GTSV)

the remaining challenges for ARCS adoption and their possible solutions. Finally, the conclusions and future research recommendations are made.

II. ARCS System for Georgia Highways

The US state of Georgia maintains 4,184 centerline kilometers of interstate highways. In 2016, an ARCS system was implemented to monitor the road asphalt pavement condition automatically. The system consists of three major components:

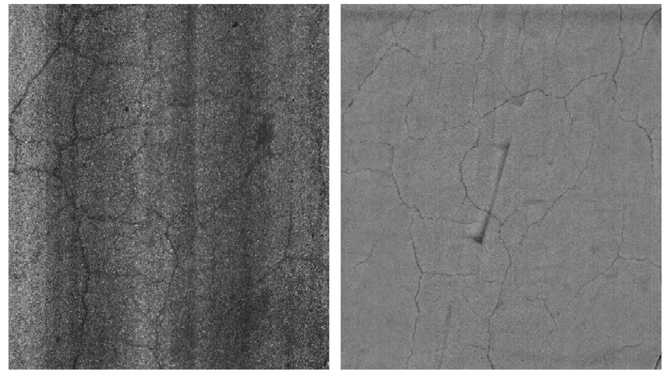
1) A data collection procedure using the Georgia Tech Survey Vehicle (GTSV) and 3D sensor technologies, collecting both 2D images and 3D range data.
2) A data processing stage that yields aggregated road condition data required by GDOT.
3) A suite of data visualization and analysis tools to aid MR&R decision-making.

A. Data Collection Procedure

The Georgia Tech Sensing Vehicle (GTSV) shown in figure 1 is used to collect the pavement surface data. The GTSV, sponsored by the United States DOT, is a vehicle equipped with emerging sensing technologies, including high-resolution cameras, 3D laser imaging, light detection and ranging (LiDAR), global positioning system (GPS), and an inertial measurement unit (IMU) [5].

The two laser imaging units from INO/Pavemetrics are mounted approximately 2 meters apart and 2.25 meters off the ground at the back of the vehicle (figure 1). The sensors are installed at a yaw angle of 10 degrees to avoid signal crosstalk. A 50-mm overlap between the coverage of the two sensors is designed to ensure complete coverage of the lane.

The resolution of the system is approximately 1 mm in the transverse direction (x-axis), 5mm in the longitudinal direction (y-axis), and 0.5 mm in the elevation direction (z-axis). With this setup, the system acquires 4,160 3D measurements per profile (2,080 per laser unit), which covers approximately 4-m across the lane. The system stores an image formed by every 1,000 profiles into a file that contains both intensity and range data, as shown in Figure 2. The intensity data in Figure 2a refers to the intensity of the reflected laser beam from the pavement surface. The range data in Figure 2b refers to the distance of the pavement surface from the sensor height. In figure 2b, darker pixels are farther from the sensor.



(a) Intensity Image (b) Range Image

Fig. 2. Pavement Images Collected by Laser Crack Measurement System (LCMS)

B. Data Processing Flow

Preprocessing steps are applied to synchronize and georeference the data collected by multiple sensors. Our research team has developed algorithms for the detection of major pavement distresses—cracking, rutting and raveling—in the past [6], [7], [8], [9], [10], [11]. The georeferenced range images from the laser scanner serve as the input for these algorithms, which detect and classify pavement distresses in these images. The camera images are similarly used for roadside features such as traffic signs [12].

For the 2016 iteration, some manual steps were also required. Manual QA/QC checks were performed to ensure data quality. For example, distresses on bridges had to be removed as they are excluded in the COPACES protocol. The COPACES protocol also collects other minor (rare) distresses, such as potholes, corrugation and bleeding. These were marked manually using a semi-automated approach. These minor distresses can be detected from the GTSV's front facing camera, which can be processed much faster manually than distresses on pavement images.

The final step is the aggregation of the detected pavement distress data to various levels defined by the GDOT COPACES protocol [2]. This results in ratings for GDOT projects which are used to prioritize MR&R operations. Additionally, the adverse effect of each type of distress on the project rating, quantified as a deduct value, is used to determine the optimal maintenance operation.

C. Data Visualization

After the data has been processed, it is necessary to provide appropriate data visualization tools to navigate the results. There are several existing data visualization tools available. However, for this project, customized visualization tools were developed.

Two examples are shown. *CrackDigitizer* (figure 3) is a QA/QC tool to add or delete cracks and joints to pavement images. *CrackDigitizer* is used to ensure the quality of crack detection results. *SlabViewer* (figure 4) is a visualization tool for displaying the properties of concrete slabs. *SlabViewer* is

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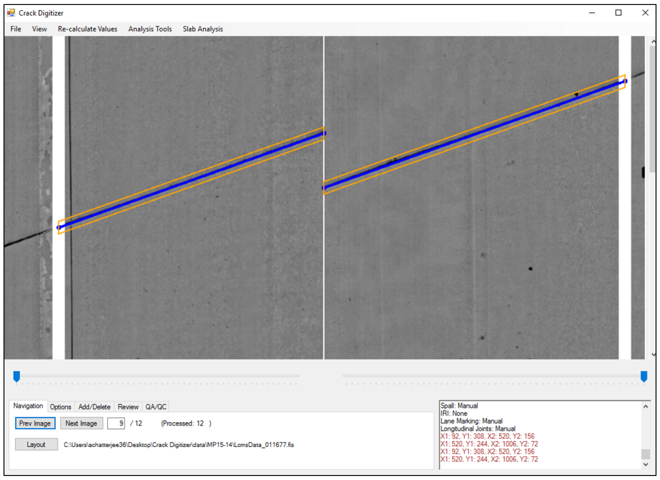

Fig. 3. Visualization tool for pavement images showing a concrete joint

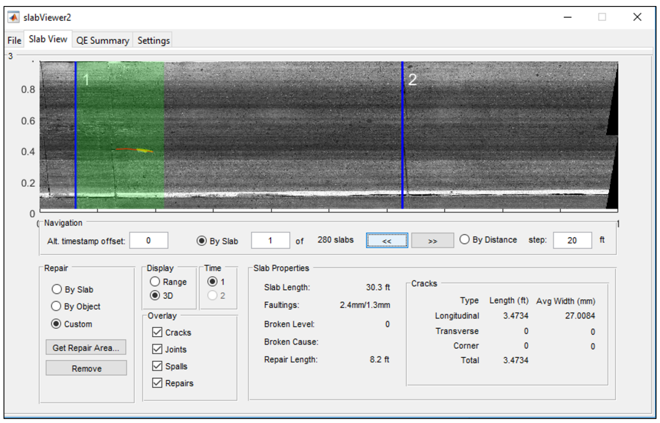

Fig. 4. Visualization tool for concrete slabs

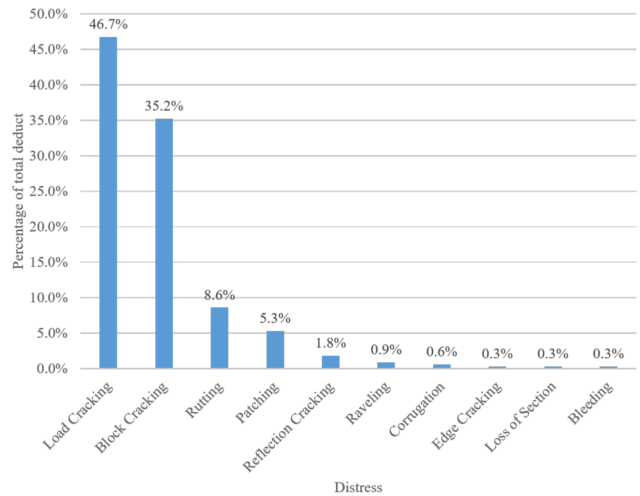

Fig. 5. Distribution of pavement distresses by deduct value

Fig. 6. Camera image of cracked pavement

useful for planning slab replacement as well as to study crack growth on concrete slabs.

III. OBSERVATIONS

Several observations were made during the development of the Georgia Interstate Highway ARCS system. Several challenges were also found which are not addressed by most ARCS research. Each of these observations and challenges are explained in the subsections below. Although the focus is on crack detection and classification, the concepts can be extended to other pavement distresses as well.

A. *Impacts of Distresses*

The COPACES protocol collects information on ten types of pavement distresses. The impact of pavement rating by these distresses is given in figures 5. Clearly, cracking has the highest impact on pavement condition, followed by rutting.

B. *Deficiencies in Image-based Approaches*

The 3D laser scanners used in the presented system are much more expensive than traditional cameras at the same resolution. Before the advent of 3D laser scanners, most crack detection algorithms operated on traditional camera images of the pavement surface. However, it has been observed that the features captured by traditional camera images face several problems with respect to crack detection.

Lighting is the most important factor for camera images. Most crack detection algorithms rely on the darkness of cracks with respect to their neighboring pixels. Depending on the lighting condition however, the appearance of the pavement and cracks change drastically, making it extremely difficult to find optimal parameters for the algorithms. Shadows of nearby objects on the pavement is another problem that crack detection algorithms have to overcome. It can be seen in figure 6 that the pavement appearance constantly changes due to lighting and shadow. 3D laser scanners overcome this problem by ignoring the visual appearance of the pavements and cracks, instead focusing on the depth of the cracks with respect to the pavement surface.

Second, 2D camera images are also affected by the appearance of the pavement itself. Depending on the material (asphalt or concrete) as well as surfacing of the pavement, the pavement texture can appear drastically different on 2D camera images. Again, 3D laser scanners reliance on depth, not appearance, helps them overcome this problem easily. It can be observed in figure 2 that the cracks are much clearer on the range image than the intensity image.

Fig. 7. Four severity levels of load cracking in COPACES

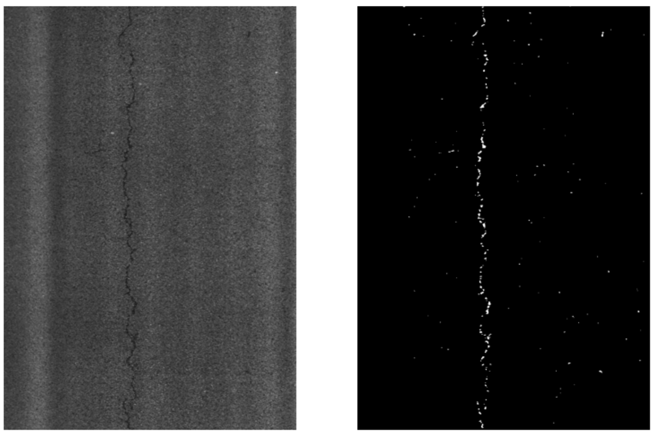

Fig. 8. Disconnected crack detection

C. Usability and Flexibility of Crack Detection Output

Despite a large volume of research on pavement crack detection, fundamental problems remain in the approaches used by most methods which make them unsuitable for use in the field.

First, it is necessary to understand the objective of pavement crack detection. For ARCS, the output of the crack detection algorithms will be ultimately used to classify and quantify pavement cracking according to a specific protocol. For example, the COPACES protocol classifies load cracking into four severity levels (figure 7). Pavement crack detection is also used in automated crack sealing [13], [14]. Another application of crack detection is to study the deterioration of pavements due to crack growth over time. For all of the above applications, it is necessary to obtain a detailed, flexible and multi-scale crack model.

The majority of crack detection algorithms are histogram or filtering based [15]. These algorithms are fast and can work at multiple scales, but do not consider the long, salient shape of the cracks. As a result, disconnected crack curves, as shown in figure 8, are a common problem. Although the disconnected crack curves can later be joined by further image processing, it generally results in a tradeoff between classifying noise as crack pixels (false positives) or losing thin cracks (false negatives).

To overcome this problem, a minimal path based algorithm [6] was used to develop the crack curves. Minimal path based techniques search for the path between the extremities of the cracks which minimize an objective function along the path.

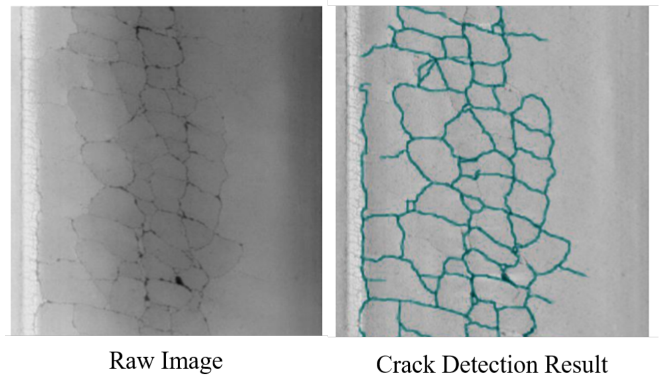

Fig. 9. Crack Detection Result

In the case of cracks, we search for the path which has the lowest depth throughout, which falls along the crack. This results in a continuous crack curve output shown in figure 9.

These continuous crack curves are then used to model the crack using crack fundamental elements (CFE) [16]. CFEs provide a detailed, flexible and multi-scale model which can be used to classify and quantify cracking according to various protocols. CFEs can also be used for accurate crack sealing path planning applications and to study crack growth over time.

D. Lack of a Performance Metric

Many automated crack detection algorithms have been developed, but they lack a standardized performance evaluation system. Hence, it is not possible to compare different algorithms. Most papers perform their own validation tests. However, these tests often fail to follow a scientifically rigorous performance metric or use a pavement image dataset consisting of diverse pavement conditions or both. In the field, crack detection algorithms are subjected to different pavement types, various lighting conditions and noise that it may not be designed to handle. [17] elaborates on this problem and presents a standardized performance evaluation system for crack detection algorithms.

For example, Figure 10 shows range images collected on three pavement types: (a) Dense-graded (DG) asphalt pavement, (b) open-graded friction course (OGFC) asphalt pavement and (c) Concrete pavement. Distress detection algorithms need to be robust enough to perform in these different pavement types. Figure 10d, 10e and 10f demonstrate the result of the relaxation thresholding crack detection algorithm on figures 10a, 10b and 10c respectively. There is no crack present. The white pixels in figure 10d, 10e and 10f have been classified as crack pixels by the algorithm. The algorithm is clearly sensitive to the pavement texture. Hence, it is necessary to consider the various pavement surface types and pavement textures that distress detection algorithms are likely to encounter in the field and design them accordingly.

A performance evaluation system is required for effective performance evaluation and algorithm improvement. This system should consist of a robust, quantitative performance

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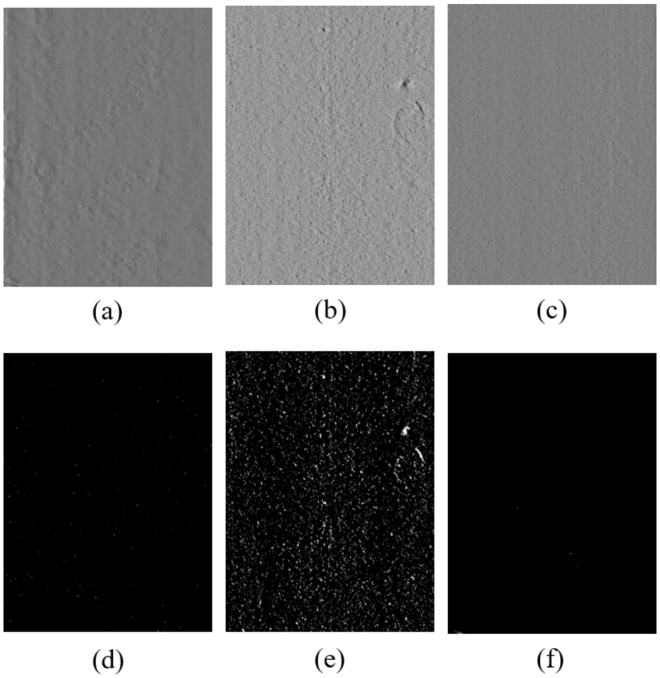

Fig. 10. Performance of relaxation thresholding algorithm for crack detection on pavement images

metric and a consistent pavement image dataset with diverse pavement textures, crack conditions, widths and severity. The system should also be able to provide a comprehensive and quantitative evaluation of crack detection algorithms. Clearly, the same concept can be extended to other distresses as well.

IV. CONCLUSION

The Georgia Interstate highway ARCS system presented in this paper requires less than 44 hours of driving on interstates to complete the data collection process. Only two members—a driver and an operator—are required to complete the survey. Typically, an annual survey can be completed in less than two weeks with this approach. Because the members do not have to stop at every mile and take measurements on-foot, this approach is much safer than the manual survey procedure. The system also improves the data quality by minimizing entry points for human error. The data visualization tools also help transportation agencies gain further insights into the ARCS results, aiding in MR&R decision-making. QA/QC measures were also taken to ensure the quality of the final results.

This paper identified remaining challenges in automated pavement distress detection. Pavement cracking has been used as an example to explain these challenges, but the concepts can be extended to other pavement distresses as well. The following research recommendations will help in the advancement of ARCS:

- Due to its sensitivity to lighting conditions and pavement appearance, camera images are not recommended for large-scale ARCS. Depth-based images, obtained from laser scanners, are independent of these factors.
- Crack detection methods should use a detailed, flexible and multi-scale crack model for their output. The CFE model [16] is one such solution.
- A standard performance measure should be developed for pavement distresses, consisting of a quantitative performance metric and a consistent dataset with diverse pavement conditions.

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