A framework for computer vision-based real-time asphalt pavement property monitoring

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Abstract –

The monitoring of the road construction operation is critical to ensure high-quality roads. This is especially the case for the compaction of the asphalt surface layer since the operation is very time-sensitive and mostly irreversible. Historically, monitoring of the asphalt compaction is limited to temperature and compaction homogeneity. While useful, these pieces of information fail to generate direct insight into the resultant physical properties of the asphalt layer (e.g., density and roughness), which are the ultimate key performance indicators. Several sensor-based methods and approaches have been proposed but these methods are particularly suited for post-construction monitoring rather than real-time application. To address this gap, this research aims to conduct a preliminary feasibility study on the use of a computer vision-based method for the real-time monitoring of the asphalt properties during the compaction. Therefore, a framework is proposed to install cameras on the asphalt roller along with a Global Positioning System (GPS) kit and track the changes of the asphalt texture at the micro level. These changes are then correlated with the progression of the compaction effort. The results indicate that the Computer Vision (CV) method can very successfully identify micro variations in the asphalt texture. This is very promising because these variations can be potentially correlated with some physical properties of the asphalt layer. While this correlation study is the future work of this research, the preliminary results already contribute to highlighting the potential of CV methods to be incorporated into asphalt compaction monitoring system.

Keywords –

Asphalt construction; Computer Vision; Texture analysis

1 Introduction

The asphalt road is the backbone of the modern transportation system. According to the Ministry of Infrastructure and Water Management of the Netherlands, the total road traffic in 2017 was 140.8 billion vehicle Kilometers [1]. The quality of asphalt roads is of vital importance to ensure the safety of passengers and also the efficiency of transportation. However, the quality of asphalt roads is a complex parameter to control as it depends on multiple factors, including but not limited to asphalt material, production procedure, base layer condition, and the intensity of use. One, often less acknowledged, factor that significantly impacts the long-term performance of asphalt roads is the quality of the construction process. The consistent and homogenous compaction of the asphalt layer at the right temperature significantly influences the longevity and quality of roads. Considering the irreversible nature of asphalt pavement construction, it is critical to accurately inspect the asphalt pavement during the construction process to spot and fix the failures in the early stages.

In recent years, realizing that early detection of failures during the construction phase could contribute to the increased service life of road pavements while also reducing its life cycle cost by up to 37% [2], on-site monitoring during the compaction process has been taken more seriously. Makarov et al. [3] has proposed a framework for compaction guidance systems that can translate the temperature and compaction count data into clear suggestions for compaction strategies. Han et al. [4] developed a construction quality evaluation framework combining building information model (BIM) and geographic information systems (GIS), focusing on the temperature, speed, and rolling frequency during the compaction phase. Zeng et al. [5] presented a real-time asphalt pavement segregation identification algorithm based on digital imaging. However, the above-mentioned research primarily focuses on the monitoring of temperature and roller behaviours instead of the real-time monitoring of the resultant physical properties of the asphalt layer (e.g., roughness and density). Or, in other words, are just indirect assessments of asphalt quality.

The real-time asphalt density and roughness monitoring during compaction has remained a bottleneck. Currently, the Ground-penetrating Radar (GPR) is considered to be an effective, feasible, and non-destructive tool for the real-time estimation of the density of asphalt concrete [6]. Wang et al. [7] proposed a signal-processing method for asphalt pavement layer thickness determination using GPR. However, the GPR-based method is strongly dependent on the asphalt material since the dielectric constant is essential for the AC density prediction [8]. For the real-time asphalt smoothness measurement, Chang et al. [9] introduced a laser-based system for the asphalt roughness identified from paver operation and roller compaction. Compared with existing as-build asphalt roughness measurements [10][11], this approach offers a solution for the real-time roughness measurement. However, due to the selection of the sensors, this approach is sensitive to typical events such as varying paving speeds(introducing vibration) and the environmental factors such as temperature, steam, and dust [9].

One possible method to address these limitations is to use computer vision techniques to directly assess the quality of the asphalt layer during construction. However, to the best of the authors' knowledge, the topic is not yet fully addressed. Therefore, this research aims to conduct a preliminary feasibility study of the vision-based real-time monitoring of asphalt properties. In this method, a geo-referenced image data collection system is designed. With the database built, image processing and data analysis algorithms will be introduced to correlate the change of asphalt surface texture during compaction with its corresponding physical properties. The remainder of the paper is structured as follows. In Section 2, the proposed computer vision-based asphalt monitoring framework is presented. Section 3 makes a brief explanation of a feasibility study taken in the real construction site will be introduced. Subsequently, the analysis of the results and discussions regarding the case study will be carried out. Section 4 encloses with a conclusion.

2 Methodology

A comprehensive geo-referenced data collection, image processing, and data analyzing framework is proposed in this section. The framework consists of 3 main stages, as illustrated in Figure 1. Schematic representation of the proposed framework.

In the initial stage, a data collection pipeline will be leveraged to collect geo-referenced asphalt pavement surface images. With the built dataset, an image processing algorithm will be developed, consisting of image pre-processing, segmentation, and result correction. In the last stage, the asphalt surface texture information generated from the image processing algorithm will be used as input for data analysis, where a machine learning method will be applied to make predictions on the corresponding physical properties of the asphalt pavement surface texture.

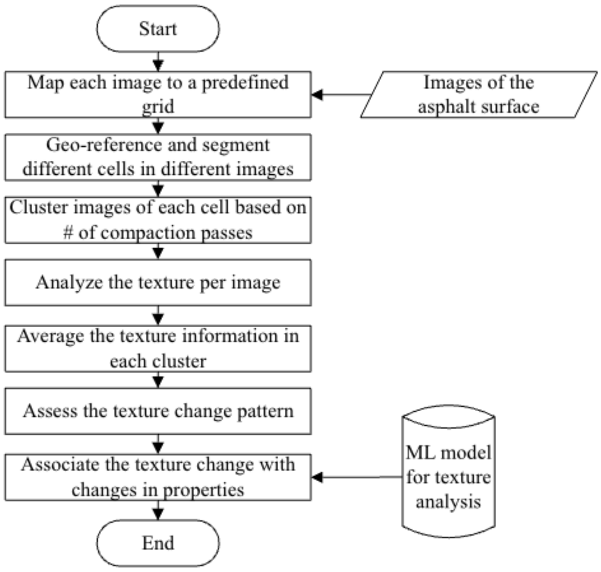


Figure 1. Schematic representation of the proposed framework

2.1 Data collection and pre-processing

The dynamic geo-referenced asphalt pavement surface texture data collection system is composed of a GPS signal receiver mounted on the top of the roller, and two cameras placed in the front of the roller and the back of the roller respectively, as illustrated in Figure 2. Schematic representation of the .

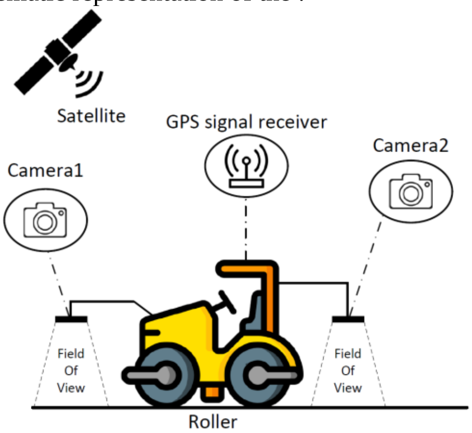


Figure 2. Schematic representation of the sensor setup

This system will take images of the asphalt surface as shown in Figure 3. The void area proportion generated from different parameter sets . This dual-camera setup allows us to track asphalt pavement surface texture changes before and after compaction.

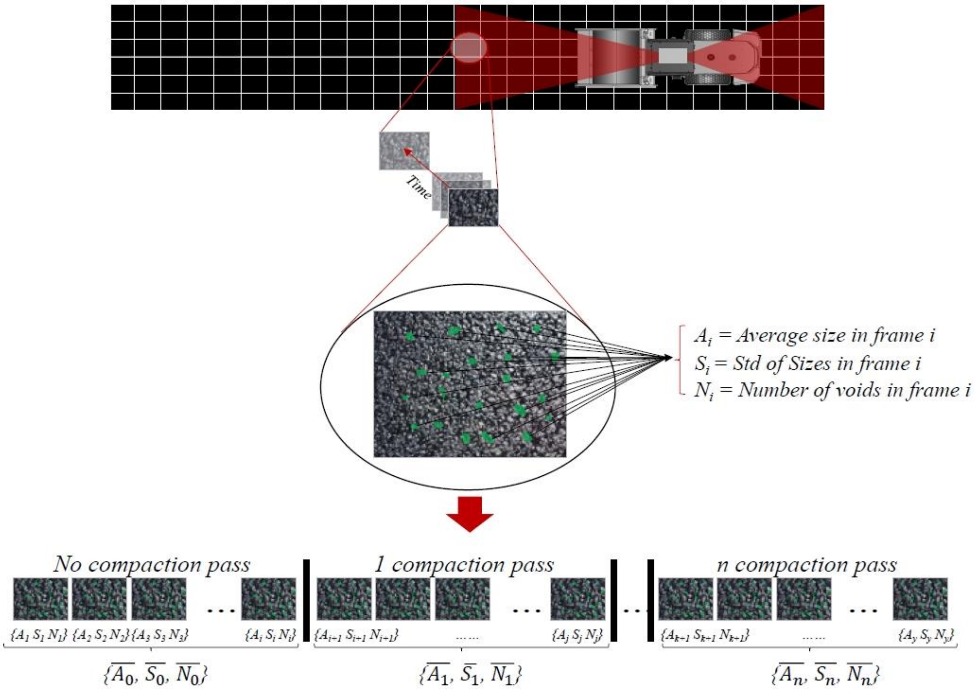


Figure 3. The void area proportion generated from different parameter sets

The raw images first need to be transformed to perspective images directly facing the surface and a compensation on the translation between the GPS receiver and the camera also need to be made. This is because the texture analysis, which is based on the shape and sizes of the voids between the aggregates, requires a uniform scale and perspective in all the images. By calibrating the camera [12], extrinsic and intrinsic parameters could be obtained. The image transformation is based on the relative orientation of the camera to the pavement surface and the translation between the camera and the GPS receiver. From the extrinsic parameters, namely the rotation matrix and translation vector, the camera's position and orientation relative to the world coordinate system could be obtained. In this phase, since the target is to convert the perspective of the camera and compensate the translation between camera and GPS signal, only the rotation matrix will be utilized and the translation vector will be replaced with a fixed translation vector between the GPS receiver and the camera. With the above-mentioned information, a homograph matrix can be computed, and with this matrix, the images captured could be projected into a perspective directly facing the surface and each image will be tagged with its rough geo-information.

Next, each raw image will be cropped into sub-images and each sub-image will be registered to a pre-defined physical grid, as shown in Figure 3. The void area proportion generated from different parameter sets. Each sub-image will be tagged with their fine geo-information. Notice that the pixel equivalent of each image is determined by (1) the installation height of the camera, (2) the orientation of the camera to the surface, and (3) the resolution of the camera[13], thus the cropped images may vary in pixel-wise sizes for different cameras.

Since the field of view (FOV) of each camera covers more than one grid, the same grid may be captured in several sequential images, and they will be clustered for result averaging. The determination of roller pass counts incorporates both image timestamps and the spatial coordinates of the roller. It is notable that sub-images that belong to the same grid from different frames will be clustered and the final output of this grid will be an average output value of all images in this cluster, as shown in Figure 3. The void area proportion generated from different parameter sets.

Sequentially, the segmentation algorithm will be conducted on the cropped images to segment the voids between the aggregates. The segmentation process is operated on each sub-image and it includes 3 steps.

(a) Brightness correction

As shown in Figure 4. Images in different lighting condition and the result of brightness correction, since the images are captured in the natural environment, the lighting conditions could vary, and the algorithm is supposed to be sufficient to adapt to different scene illuminations.

With dynamic range compression, the images taken from different illuminated scenes are expected to produce good spectral tonal rendition and be tuned into similar brightness conditions. The Multiscale Retinex (MSR) [14] algorithm, one of the most popular and proven to be significant brightness correctness algorithms, is applied in this study. In this stage, the redundant information of the raw images such as dirt on the surface will be removed and the essential texture information (aggregate edges) will be preserved and enhanced. Figure 4 shows the result of brightness correction.

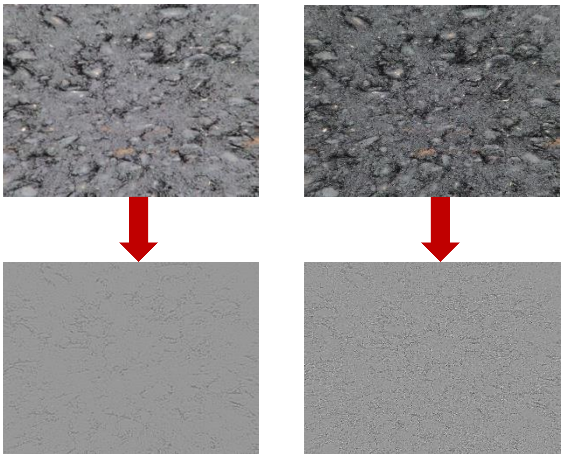


Figure 4. Images in different lighting condition and the result of brightness correction

(b) Segmentation

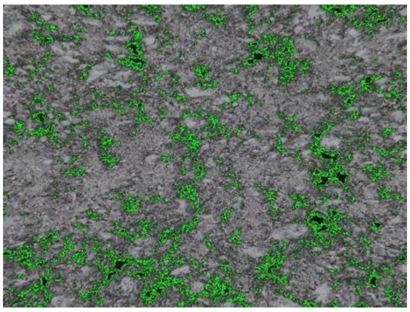
The aggregates and the voids between them exhibit different grayscale values in the images. The voids are dark areas in the images while the aggregate areas display larger grayscale values. Considering this grayscale distribution pattern, thresholding can be applied to segment the voids. Since the raw images are corrected to a similar brightness condition, a global threshold value could be set to traverse each pixel in the images and binarize the image. If the grayscale value of the pixel is greater than the threshold value, it is considered to be the aggregate and the value of this pixel will be set to 0, otherwise, it is considered as the target voids and will be set to 255. The threshold is calculated with Equation 1.

$$threshold = mean - a * deviation \tag{1}$$

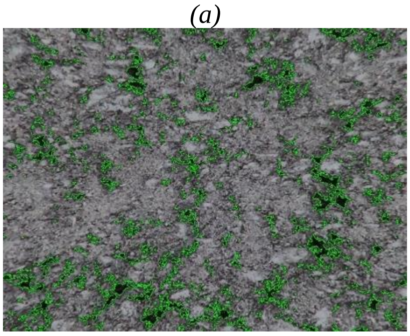
Where $mean$ refers to the mean gray value of the image, $deviation$ refers to the deviation of the gray value in the image and a refers to an experience-based parameter, which will be explained in Section 3.

(c) Segmentation result correction

The segmentation result is based on the grayscale values and small connected components can be found in the segmented results. Ideally, the fine textures in the small connected components are expected to offer detailed information on the asphalt pavement surface. However, they negatively impact the performance of texture analysis since the fine texture structure of pavement image has a marginal effect on the physical properties of the asphalt pavement (e.g., roughness) [15] but increases the computation cost of analysis. Also, some of the small connected components represent noises that affect the accuracy of subsequent processing steps. To refine the analysis and emphasize representative asphalt surface texture patterns, small and isolated regions will be removed according to their size and morphological [16] connectivity. The comparison between the initial segmentation results and the results after correction is shown in Figure 5. The contours of the segmented voids are labeled with green polygons. It is worth mentioning that the “voids” in this work refer to the void area between the aggregates on the surface, which display dark regions on the images, and they could represent the surface texture of the asphalt layer.



(a)



(b)

Figure 5. An example of the result of segmentation (a) before and (b) after correction

2.2 Data analysis

The segregated void areas will be mapped into quantified physical properties, which will be considered as a regression problem. The input of the regression algorithm includes handcrafted features such as the quantity of void areas and the total area size of the voids, and also the high-dimensioned features generated from a pre-trained convolutional neural network (CNN). With the input, the machine learning algorithm is expected to deliver the quantified physical properties.

2.2.1 Texture analysis

The output of the image processing step is a binary image, with the void areas set to 255 and the background set to 0. The mask image, representing the features of the original image, will be serialized into a vector as the input of the machine learning algorithm.

Note that the images from each grid are clustered and their feature vectors will be averaged and then forwarded to the next step as the input feature of the machine learning algorithm.

2.2.2 Correlating texture properties with physical properties

After getting a vector as the input of the machine learning algorithm, the output of the machine learning algorithm is determined to be the corresponding physical properties of the asphalt surface area. During the training and validation stage for the machine learning algorithm, this data will be collected on-site or in a lab test. The training and validation process will follow a regular machine learning algorithm development process.

3 Experimental results and discussion

Since the core assumption of this research is that there is a trackable change in the asphalt pavement texture when the compaction happens, the preliminary feasibility validation for this research focused on the texture change detection. Two case studies were conducted in two different road construction projects in cities of Almelo and Winterswijk, the Netherlands. On each project sites, we collected data on 4 different sampling stations. The data collection station for this preliminary verification consists of a stationary camera placed on the side of the road and capturing 1 image every 10 seconds, as shown in **Error! Reference source not found.**.

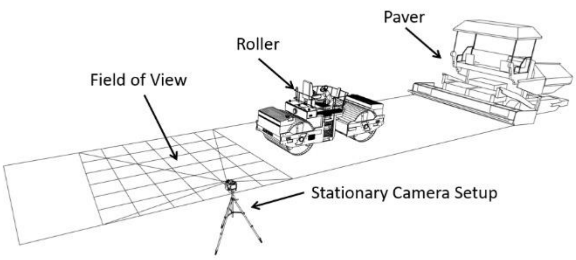


Figure 6. The experimental setup

The images captured within the compaction intervals are expected to display the same or similar pattern in texture, and images captured right before and after compaction are expected to display different texture patterns. Different models of cameras were used for each project, to assess the sensitivity to the camera model. The case studies aimed at (1) capturing the asphalt pavement surface images for the same area experiencing different rounds of roller pass, (2) extracting the surface texture, and (3) providing a quantified analysis of the texture indicating its change.

Following the steps introduced in Chapter 2.1, the total void area after each compaction was detected. As mentioned above, a few key parameters are crucial for the detection results. The sensitivity of the model to these parameters is shown in Figure 7.

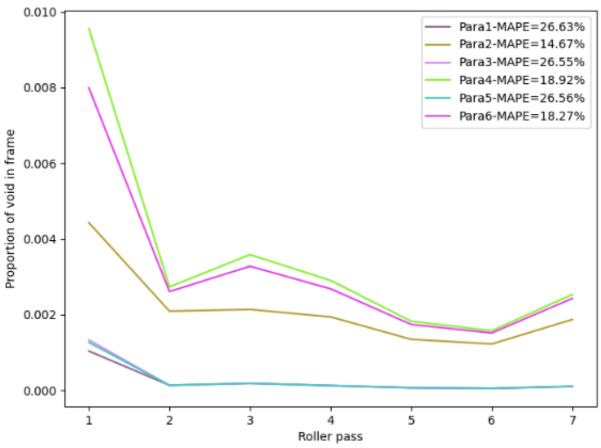


Figure 7. The void area proportion generated from different parameter sets

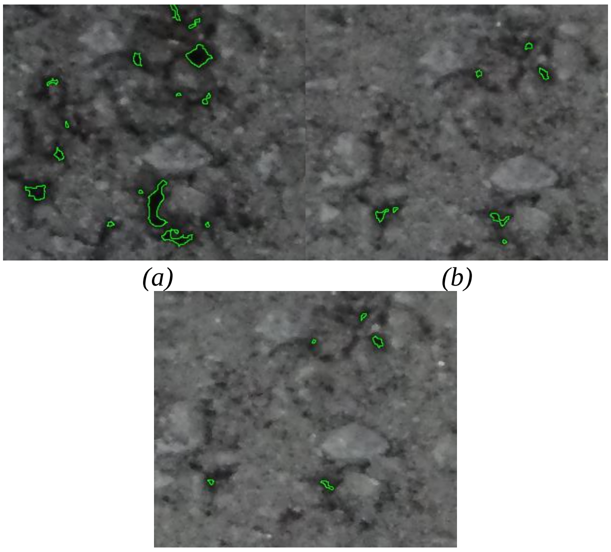
As shown in this figure, while all graphs indicate an overall negative exponential pattern, the magnitude and smoothness can vary. Given that the physical behaviour of asphalt conforms to a negative exponential trend, a negative exponential curve fitting was employed as the objective function to optimize the segmentation parameters. The mean absolute percentage error (MAPE), as indicated in Equation 2, was used for the evaluation of the fitting result.

$$MAPE = \frac{\sum \frac{|A-P|}{A} * 100}{N} \quad (2)$$

Where N refers to the number of sampling points, A refers to the actual value and P refers to the predicted value.

The result shows that the MAPE of the designed algorithm could reach 14.67% with an optimal set of parameters, which indicates that the variation of the segmented void area to the roller pass could be well-fitted to a negative exponential function. As the assumption is that the texture of the asphalt layer surface exhibits a similar trend as some of the mechanical or physical properties of the asphalt to the roller passes, which is known to be a negative exponential pattern, this result proved that the segmentation algorithm is sufficient.

An example of the detection results of a sampled area after different roller passes is shown in **Error! Reference source not found.**. The results below is generated from the optimal parameters.



(a) *(b)*

(c)

Figure 8. An example of the segmentation results (a) right after paving, (b) after 5 rounds of compaction, and (c) after 10 rounds of compaction

Figure 9 presents the variation of the total void area in relation to the compaction passes for different test locations. As shown in this figure, there is a clear degrading pattern of the total void areas with respect to compaction passes. This can be construed as a strong indication that changes in asphalt textures are tracible and can be captured by computer vision. This clearly points to the potential that the texture analysis could be correlated with the development of different physical properties.

It is worth noting that the ranges of the total void area percentage in each frame are expected to be more or less the same, while it varies in our test. One potential reason for this variance is that the tests are done on different construction sites where different materials are used and each material has different properties. Another possible reason for this variance is that the distance between the camera and the surface is not precisely adjusted and therefore different from one station to another. At a larger distance, due to the lower resolution and the filtering strategies, some of the small voids could be undetected. Since the feasibility analysis is based on each camera in a time series, this factor does not affect the result of this experiment. However, it needs to be considered in future research when images from mobile camera (i.e., mounted on equipment) are used for analysis.

Also, during the validation, we found some factors may interfere with the image quality and lead to an unsatisfying result if the cameras are installed on the roller. The factors are (1) the water on the rollers will result in the steam and it will render the images blurry, and (2) the vibration of the roller may result in blurry images. Thus, the above-mentioned factors need to be considered when installing the camera on the rollers and extra mechanical designs such as stabilizer need to be added to the system.

4 Conclusion

This research proposed a framework for the vision-based monitoring of the asphalt properties during construction. As a preliminary validation of the idea, the asphalt pavement texture analysis has been done with a stationary camera set. The preliminary results exhibit a negative exponential pattern on the total void area of the asphalt surface as the roller passes increase. The negative exponential trend follows the theoretical trend of changes in many of physical and mechanical properties of the asphalt layer. This indicates that this method can be leveraged to correlate these properties with the changes in the texture of the asphalt during the construction. The application could be a real-time system where operators can be informed about the condition of the asphalt layer during the operation to adjust their operational strategies.

It should be highlighted that while vision-based monitoring of the asphalt condition in the operation phase (e.g., for detecting cracks and potholes) has been extensively studied, to the best of the authors' knowledge, the use of texture analysis during the construction process and the correlation of the texture change with the progression of the physical properties of the asphalt layer has not been studied.

This research will be further pursued by (1) installing the cameras on the rollers and considering the environmental interferes this may have on the images, and (2) correlating different physical properties of the asphalt layer with variation of the asphalt texture during the construction.

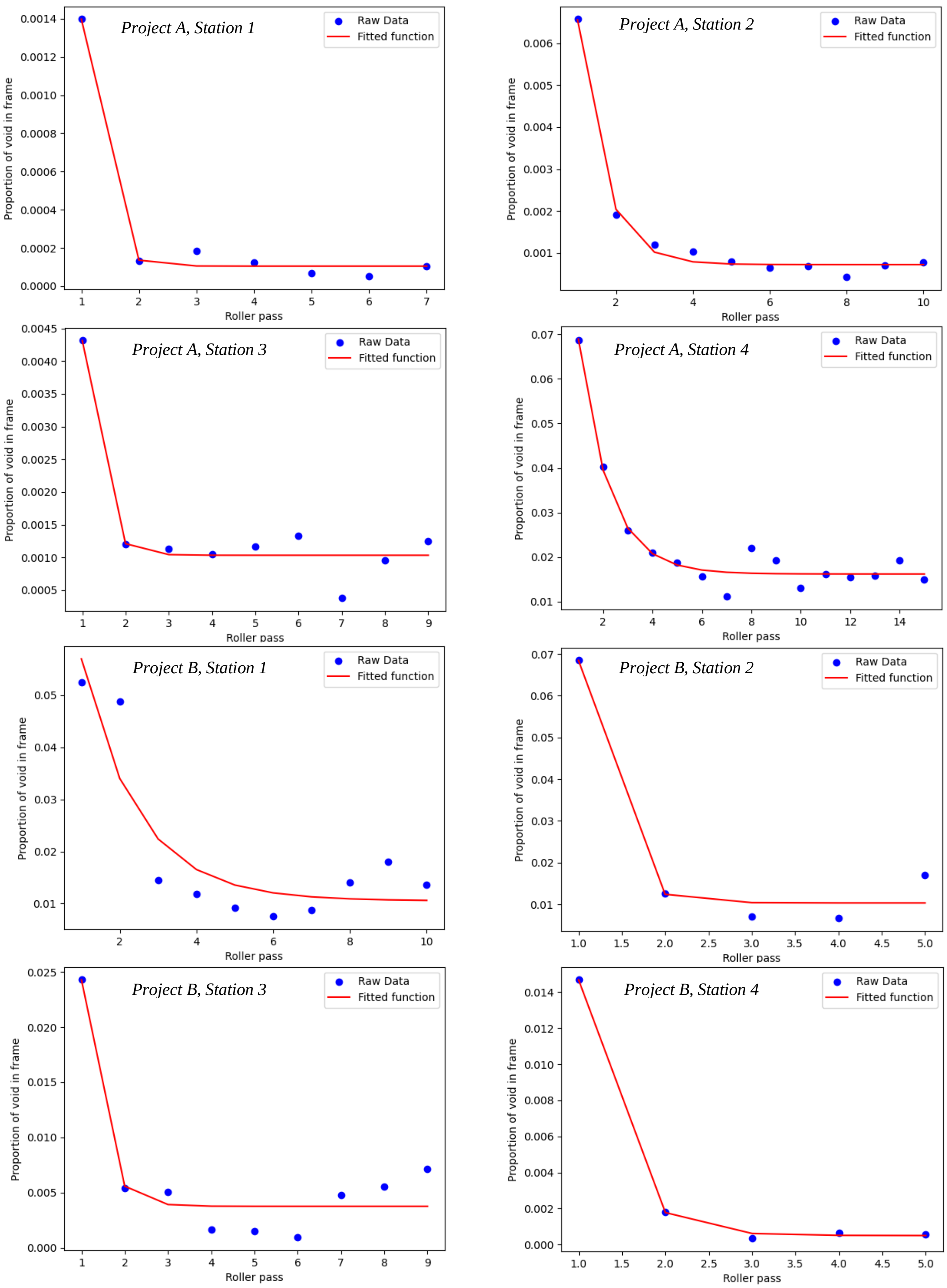


Figure 9. Fitting result on the void area after compaction

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