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Tack Coat Inspection Using Unmanned Aerial Vehicle and Deep Learning

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Abstract: Tack coat is a thin layer of asphalt between the existing pavement and asphalt overlay. During construction, insufficient tack coat layering can later cause surface defects such as slippage, shoving, and rutting. This paper proposed a method for tack coat inspection improvement using an unmanned aerial vehicle (UAV) and deep learning neural network for automatic non-uniform assessment of the applied tack coat area. In this method, the drone-captured images are exploited for assessment using a combination of Mask R-CNN and Grey Level Co-occurrence Matrix (GLCM). Mask R-CNN is utilized to detect the tack coat region and segment the region of interest from the surroundings. GLCM is used to analyze the texture of the segmented region and measure the uniformity and non-uniformity of the tack coat on the existing pavements. The results of the field experiment showed both the intersection over union of Mask R-CNN and the non-uniformity measured by GLCM were promising with respect to their accuracy. The proposed method is automatic and cost-efficient, which would be of value to state Departments of Transportation for better management of their work in pavement construction and rehabilitation.

Key words: tack coat, inspection, unmanned aerial vehicles (UAVs), Mask R-CNN, Grey Level Co-occurrence Matrix (GLCM)

1. INTRODUCTION

Tack coats are thin liquid asphalt applied to provide bonding between the top surface and the pavement lifts. The adhesive bond between the two layers helps the pavement system to interact as a single unit [1] and enhances the adhesion between interlayer surfaces [2]. Sufficient tack coat layering has strong adhesive bonding and shear strength resistance that can support heavy truckloads and prevent pavement displacement [3]. Guidelines have been provided to the highway agencies for the tack coat applications to enhance the interface bonding strength, including optimum application rate, the temperature of the application rate at 55°C and 25°C depending on the type of tack coat, selection of proper equipment, and uniformly layered which visually assessed by inspectors [2, 4]. The guidelines for tack coat layering inspections are varied among the state Departments of Transportation (DOTs). The decisions for the visual inspections are determined based on experience, judgment, and convenience [5], this shows that visual inspection has also no specific measurement for uniformity determination. Tack coat layering is an essential step in the pavement construction process. Therefore, the guidelines on tack coat quality control/assurance (QC/QA) and construction practices need to be unified for the users [6].

The existing conventional tack coat application assessment is performed by field inspectors. Like road surface assessment, the manual observation inspection process is time-consuming, highly expensive, and requires a high level of labor work [7]. Experts have developed models to analyze the critical stresses and strains at layer interfaces affected by different variables (such as layer thicknesses, temperature, and loads) [8]. In [9], the researchers used the developed BISAR software to measure the bonding between the layers and the effect on its surface specifically on pavement fatigue life. Another approach used the ALIZE program to measure the effects of bonding on the pavement service life. It was proven that the lesser the bonding strength between the layers, the lower the service life of the pavement is [10]. Most of the existing solutions were developed to determine the bond strength of the interface layers and their effects after road construction. To ensure better bonding between the layers during the construction, uniformity application is essential for achieving desired interface bonding strength [11]. Until now, not a lot of computer vision-based models have been developed to analyze the uniformity of layering of tack coats before the overlay.

The DOTs have adopted Unmanned Aerial Vehicle (UAV), commonly referred to as drones, as one of the non-destructive visual inspection equipment [12]. This technology has been utilized in the construction and transportation industries for many purposes such as inspections of civil structures. The capability of the drone technology, equipped with a broad range of sensors and cameras, to collect visual data of civil structures quickly at a lower cost has gained remarkable interest [13]. This method is considered to be safer, faster, and more efficient compared to ground data collection [14]. Thus, our approach is promising to accelerate the inspection by using UAV to collect images. It applies a combination of two computer vision-based processes on the UAV-captured images for tack coat region detection. Then, it analyzes the texture of the segmented region and measures the uniformity coverage using Grey Level Co-Occurrence Matrix (GLCM).

2. RELATED WORK

Deep learning, as a subset of machine learning, has been applied in various applications for automatic object detection. The state-of-the-art of deep learning techniques especially the Convolutional Neural Network (CNN) have been vastly used for object recognition and segmentation of the detected object pixels [15]. Due to limited studies done on the vision-based application for non-uniform tack coat layering assessment, most of the studies done are based on automated system application on surface distress detection. For civil structure inspections, most CNN-based approaches on the UAV-captured images are for extracting features of surface distress detection on roads [16] and bridge structures [13]. In [14], researchers classified different types of distress on the pavement by using bounding boxes and then implementing U-Net to determine the severity of each detected distress.

Similarly, in [17], CNN-based object detector, Fast R-CNN is used to draw bounding boxes around the type of distress being detected. Usually, road surface images captured by UAVs contain other objects from the surroundings like trees, road ancillary structures, construction equipment, etc. Oliveira et al. in [18] developed a binary segmentation module, VGG16, to segment roads from the surroundings. This method detected the surface road pixels and segmented the region of interest. Meanwhile, Mask R-CNN was developed on top of Faster R-CNN and is an instance segmentation of deep learning methods. In addition to the bounding box and predicting the labels, Mask R-CNN will also produce a mask over the detected object [19]. To detect damage in bridge inspections, Mask R-CNN was applied to investigate UAV-captured images by segmenting the object and detecting the distress accurately [13]. While some simple image processing has proved to be efficient for detecting non-uniformity when images contain solely one object. GLCM was used to analyze the texture variations of the road surface. Since images were taken by UAV, the captured images have enough exposure that non-distressed regions have lower contrast while distressed regions have higher contrast [20].

3. METHODOLOGY

We developed a novel tack coat image analysis framework consisting of two main modules including tack coat region segmentation and automatic uniformity coverage measurement. The tack coat dataset was collected from two sources: the internet and using the drone. Since model training requires a large dataset, the major portion of the dataset was collected from the internet of tack coat, seal coat, or dark asphalt of newly built asphalt roads and driveways. Drone-captured images were taken perpendicular to the longitudinal road of dark areas of new asphalt layers, and parking lots. Due to restricted access to public areas, our freedom of collecting images on public roads or parking lots is very limited for using drones. Images were taken mostly at the same place at different heights between 5-30 ft. to increase the dataset for model training.

3.1. Segmentation of tack coat region

This proposed framework is to detect the tack coat region from each image. It was challenging to segment solely tack coat region from images that had many captured objects in the field (including construction equipment, workers, trees, and even shadows) by using traditional segmenting methods. The deep learning neural network method, Mask-RCNN, was implemented for the segmentation process. Mask R-CNN was originally trained in a large Coco dataset [21]. A total of 2100 images were collected, and the data was split into training, validation, and test sets according to an 80%-10%-10% random split. The data were manually labeled with one classification “tack coat” using VGG Image annotator by drawing polygons around the regions. The model was retrained using transfer learning with the learning rate and momentum of 0.01 and 0.8, respectively. Other hyperparameters of Mask R-CNN like the batch size and the number of epochs were set to 15 and 75, respectively. The predicted region was compared with the manual ground truth label. To evaluate the performance of the trained classifiers, two metrics were used as Intersection over Union (IoU) and Recall. The IoU measures the overlapping between the ground truth label and the predicted label. While for the Recall, calculates the number of predicted boxes in the image from the ground truth boxes [22]. The equations for these metrics are shown below, where **Tp** = True Positive, **Tn** = True Negative, **Fp** = False Positive, **Fn** = False Negative.

$$IoU = \frac{Tp}{Tp + Fp + Fn} \tag{1}$$

$$Recall = \frac{Tp}{Tp + Fn} \tag{2}$$

To just visualize a contour line around the predicted object, the masking was removed. Mask R-CNN mask is in a form of Boolean (True/False). The detected region was segmented from the surroundings by converting the Boolean form of the mask to 0s and 1s. Each predicted mask was used to multiply with the original image to make the non-tack coat pixels become zero. The application of the segmentation module is to limit texture analysis of the non-uniform measurement to the tack coat region.

3.2. Uniformity coverage measurement

This step is applying simple image processing methods to the segmented tack coat image. To determine the percentile coverage for the tack coat coverage, the GLCM textural analysis method was used to analyze the texture based on the intensity variations. The segmented greyscale image was converted into an 8-bit image with 256 grey tonal levels. The patch pixels were discretized based on the grey tonal level and formed a GLCM matrix on the frequency of two groups of pixel combinations occurring in the window. The window's first position was placed over the top left of the image and moved over until the image is fully covered [23]. Inside the window, the patches were defined by the patch IDs, and each image had 4096 patches. The offset for the reference patch and the neighbor patch was set at a distance of 5 within 0 angles from the reference pixel. The GLCM matrix was normalized to calculate the texture features such as energy, homogeneity, correlation, as well as the GLCM, mean (μ), and variance (σ^2). N_g is the number of gray levels in the image and $g(i, j)$ is the element i, j of the normalized symmetrical GLCM.

Energy measures uniformity. High energy occurs when the distribution of gray level values is constant such that energy is 1 for a constant image.

$$Energy = \sqrt{\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} g^2(i,j)} \tag{3}$$

Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity is 1 for a diagonal GLCM.

$$Homogeneity = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{1}{1+(i-j)^2} . g(i,j) \tag{4}$$

Correlation measures the correlation between the reference and the neighbor pixel over the whole image. Range from -1 (negatively correlated) to 1 (passively correlated).

$$Correlation = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i - \mu).(j - \mu).\frac{g(i,j)}{\sigma^2} \tag{4}$$

The calculated outcome of each texture properties values was normalized to be ranged between 0 and 1 using the min-max normalization method.

$$X_{new} = \frac{X_{i-(X)}}{(X)-(X)} \tag{5}$$

To determine the difference between the uniform and the non-uniform coverage. The threshold was set based on the GLCM texture properties for each patch. The uniformity percentage between "uniform" and "non-uniform" was calculated by the percentage ratio. Where N_u represents the number of uniforms and N_{non} represents the number of non-uniform patches.

$$Uniformity\ (\%) = \frac{N_u}{N} * 100\% \tag{6}$$

$$Non-uniformity\ (\%) = \frac{N_{non}}{N} * 100\% \tag{7}$$

4. EXPERIMENT AND RESULTS

Images were collected using a DJI Phantom Pro+ V2.0 quadcopter drone with a 5.5" FHD screen attached. This technology is equipped with a GPS and camera sensor that can shoot 4K/60 fps videos and 20 MP photos. It has a flight time of up to 30 min. Our software was implemented using

Python 3.6.13 with libraries including Keras 2.1.6, TensorFlow 1.15.0, h5py 2.10.0, SciKit-learn 0.24.2, Pandas 1.1.5, and Numpy 1.19.5. Our software was run on Jupyter notebooks.

4.1. Evaluate the model performance using IoU and Recall

The region of interest is detected in the red contour line while the ground truth labeling is shown in green (see Figure 1). In the image, it can be observed that the dark region in the images has other objects like trees, construction vehicles, and other surroundings, but the Mask R-CNN model classifier could successfully segment the region of interest in that case. The accuracy of the outcome of the model was evaluated, the predicted segmented region of each image was compared with the ground truth label. The highest rate of IoU value for the tested images was 0.93 and the IoU average was 0.857.

Figure 1. Dark coat region detection using Mask R-CNN

4.2. Texture analysis on segmented images

For the textural analysis, the GLCM properties such as contrast, dissimilarity, homogeneity, energy, correlation and angular second moment were calculated. Contrast and dissimilarity are positively correlated to each other but homogeneity, energy, correlation, and ASM are negatively correlated with the first two properties. So, among these properties, we can consider a single property to analyze the textures of the tack coat region to determine the uniformity on the road surface. Three chosen properties were used to measure the surface texture of the tack coat region. The threshold category for uniform and non-uniform coverage was manually set based on the histogram of each texture properties. For uniform category was set for every patch value that was greater than 0.4, 0.3, and 0.2 for energy, homogeneity, and correlation, respectively. Any lesser value was categorized as the non-uniform patch. The result shown in figure 2, this region has a uniformity coverage of 59.8% and non-uniformity coverage of 40.2%. The measurement of the overall uniformity and non-uniformity was benchmarked with ground truth from experts' knowledge. It showed that the result of texture analysis was acceptable. The performance will later be evaluated when the rating model is built.

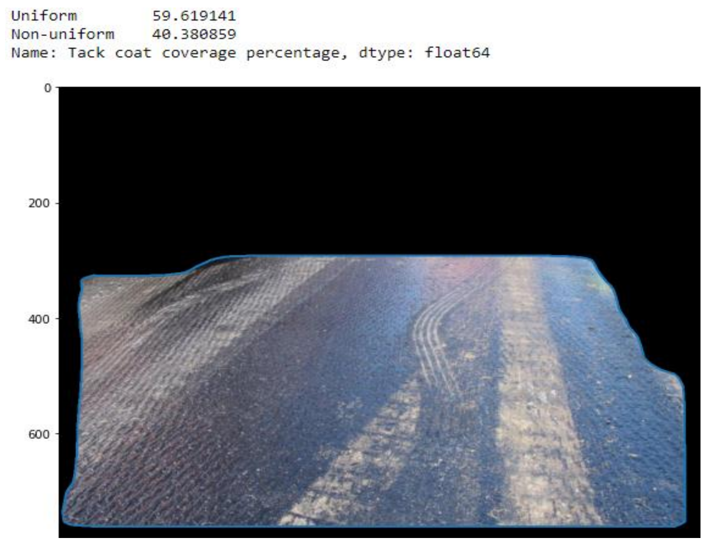

Figure 2. An example for the figure

4.3. Compared with the state-of-the-art

As there is a lack of a publicly available dataset to compare the performance of our proposed methodology with others, we looked for similar existing solutions with other deep learning methods. Mask R-CNN is an instance segmentation where the existing segmentation methods are semantic segmentation. The proposed framework is a tack coat segmentation method while the existing state-of-the-art methods is using deep convolutional neural networks architectures for segmenting unpaved roads from the surroundings on unpaved road dataset. Khiliji et al. in [24] applied VGG 16 and Mobilenetv2 to analyze pavement distress on the unpaved segmented road. The overall performance of VGG 16 and Mobilenetv2 had IoU rates of more than 91%, and Mask R-CNN had IoU rate of 85%. The instance segmentation method had lower accuracy comparing to the two semantic segmentations. This might be because the training data were mostly collected from internet while the other two methods were trained with only unpaved roads data which were mostly collected in person. However, the Mask R-CNN performance measured by recall was 96% while VGG 16 and Mobilenetv2 were 95.3% and 95.0%, respectively. Since the tested images all contain only one region and one class, the precision score was 1.0 for most of the images. It could be inferred that Mask R-CNN showed competitiveness with other state-of-the-art approaches.

5. DISCUSSION AND CONCLUSION

The key contribution of our work is to introduce computer vision methodologies in existing tack coat layering assessment techniques to make it faster and more accurate. The method showed competitive performance on the problem compared to other automated solutions. Developing a unique feature space in terms of GLCM properties as a computational model to analyze the segmented road surfaces. The outcome of this method yields percentile results which can be used for numerical judgment.

Training images contain non-uniform and uniform regions. There were misdetections of similar textures such as curbs, sidewalks, and roads parallel to the tack coat region. Detection of false positives on testing caused IoU of Mask R-CNN to drop. Besides that, the model was trained mostly with images collected from the internet, taken by people on the ground; it was noted that images taken perpendicularly at a lower altitude around 5-10 ft. have low IoU value as well. These errors could be reduced if the model were trained using a large dataset. The application of GLCM is to measure the uniformity of the road surface which showed very promising results in the field. Through our comparative results were intuition-based, which opens the door for further research in the area. In the future, we have a plan to extend our proposed method for in-depth quantitative analysis on the tack coat inspection assessment and locate the non-uniformity region.

Despite the notable contributions of using drones for tack inspections, it has limitations as well. Drone images are high-quality images compared to the data collected from the internet; however, it has a short life battery and can even be shortened by harsh weather, camera exposure to the changes of the weather [25]. According to the FAA regulations, must fly only during the day, must be registered and operated by a licensed pilot, must not fly from a moving vehicle, and must not fly over people [26]. To ensure accuracy, there are more advanced deep learning models already proposed for instance segmentation. So, the performance of the proposed model could be improved in terms of space and time complexity.

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