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STRIPPING ASSESSMENT OF ASPHALT COATING USING K-MEANS CLUSTERING AND SUPPORT VECTOR MACHINES

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Abstract: Stripping of the asphalt coating is a major moisture-related damage in hot mix asphalt pavements, which deteriorates the bond between the asphalt cement and aggregate particles. This issue could initiate many forms of asphalt pavement distresses, such as ravelling. Static immersion is a common testing method to assess the stripping of asphalt cement cover from the aggregate particles in a submerged condition, but since this assessment depends on the visual judgment of technicians, its accuracy and reproducibility have been disputed by professionals and research community. Image processing and machine learning methods have proven to be reliable tools and have the potential to provide consistent and accurate results in this test. This paper introduces a computer vision-based system to estimate the stripping of test samples processed in the static immersion test. This system employs series of image processing methods to enhance the lighting of the images and to correct specular highlights. Then the pixels on the enhanced images are segmented using the k-means clustering algorithm, and the resulted clusters are classified using linear support vector machines to determine the number of pixels belonging to the coated and uncoated areas. A set of experiment was carried out to evaluate the performance of this system, in which the machine-measured results did not have a significant difference with the manual assessments with a mean difference of 2.74%.

1 INTRODUCTION

The moisture damage susceptibility of hot-mixed asphalt (HMA) pavements is an important issue in durability of the highway networks, which is particularly important in the regions with high annual average precipitation (Liu. et al. 2014). Moisture-related damages can be defined as the degree of performance loss in an asphalt pavement due to moisture. The damage process initiates by moisture transportation into the system and causes cohesive and adhesive failures in the asphalt coating (Caro et al. 2008).

Stripping is the detachment of asphalt cement coating from aggregate surface and causes different forms of distress in asphalt pavement (Kakar et al. 2015; Mehrara and Khodaii 2013). Therefore, a number of research studies investigated the stripping damage in asphalt pavements, which includes investigation of damage mechanisms, field studies, laboratory experiments for prediction and controlling stripping damages, and analytical modelling of the moisture-related damages (Mehrara and Khodaii 2013; Caro et al. 2008). Moisture penetration into the mix is the first stage of damage and the response of the pavement could manifest in different forms, such as stripping, ravelling, and hydraulic scour (Caro et al. 2008).

There are two main types of laboratory experiments to evaluate moisture sensitivity of HMA mixtures, including test procedures for loose and compacted mixtures. Static immersion test MTO LS-285 (Ministry of Transportation of Ontario 2018) and the boiling water ASTM D3625 (American Society for Testing and Materials 2018a) are the main instances in the first group, and immersion compression ASTM D1075 (American Society for Testing and Materials 2018b) and Modified Lottman Test AASHTO T283 (AASHTO 2018) are example test methods carried out on compacted mixtures.

The amount of retained asphalt cement coating measured in the static immersion test is usually used to assess the effectiveness of anti-stripping treatments and investigate related durability problems of HMA, such as raveling. The outcome of this test is expressed as "retained coating", which is the approximate percentage of the aggregate surface that retained asphalt cement coating. This is a manual process, which is based on visual assessment of the visible portion of the mixture. Although the test procedures designed for the loose mixtures are simple and require basic tools available in most asphalt laboratories, the test samples are visually assessed and the subjectivity of the assessments by unexperienced evaluators can negatively affect the consistency of the results (Källén et al. 2016; Amelian et. 2014; Källén et al. 2012).

Image processing algorithms provide reliable options to replace visual assessment, specially in controlled environments, because they offer better accuracy, speed, consistency, and lower cost compared to manual assessment (Andreopoulos and Tsotsos 2013). Civil engineering research community has been also utilizing image processing algorithms to improve assessment of asphalt pavements. Field assessment systems and laboratory-based methods are two main groups of research in this area. Field assessment systems aim at detection of pavement distresses, such different cracks and potholes. A main challenge in these methods is the varying lighting conditions (due to daytime, weather condition, and shadows), and therefore pre-processing techniques are typically used to enhance lighting of the images (Koch et al. 2015). Then the distresses are mainly identified based on the assumption that the defective regions are darker than the normal pavement. Different image processing algorithms, such as thresholding, edge detection, and iterative clipping methods (Koch et al. 2015), deep learning (Zhang et al. 2018), and support vector machines (Hoang et al. 2018), were used to detect cracks, whereas segmentation methods, such as watershed (Tsai and Chatterjee 2018), fuzzy c-means (Ouma and Hahn 2017), and semantic texton forests (Radopoulou and Brilakis 2016), were employed to detect potholes and patches.

The laboratory-based methods focus on improving existing test procedures by producing more accurate and consistent test results. In particular, image processing methods were developed to estimate asphalt cement coverage of aggregate particles. Earlier research efforts used simple methods, such as thresholding in grayscale frames, to estimate retained asphalt cement coating in mixtures (Kim et al. 2012; Merusi et al. 2010). Thresholding on YUV colour-space showed better performance than Red-Green-Blue (RGB) colour space in the removal of the shades (Lantieri et al. 2017). But simple thresholding should be done manually and it is problematic in dark aggregate samples with similar colours to the asphalt cement. Moreover, thresholding methods are not able to distinguish shadow areas and specular highlights, thus special illumination systems were proposed to reduce these issues (Yuan et al. 2015; Merusi et al. 2010).

Colour transformation and segmentation methods were used in later studies to estimate the stripping in loose mixtures (Källén et al. 2016; Yuan et al. 2015; Källén et al. 2012). Test sample particles should be spread on a plain background (with a plain colour such as blue) to enable thresholding module to isolate mixture particles. Then a classification method, such as k-means clustering, could be employed to segment the pixels of with close intensities, thus the number of pixels belonging to each cluster can be counted (Källén et al. 2016). All of these research efforts, however, change the original test procedures, because the operator has to manually spread selective particles on a board with a plain colour. In addition, some of the main processes, such as thresholding or deciding on the class of clusters (stripped or coated), were carried out manually.

This paper aims at addressing these limitations by proposing a system that does not require changing original test procedure (i.e. spreading samples on a plain background). In particular, this system is proposed to automatically assess the test results of the Ministry of Transportation Ontario's (MTO) stripping by static immersion test procedure LS-285 (Ministry of Transportation of Ontario 2018) without changing its original procedure, in which the sample particles have to remain in the beaker. In addition, this paper proposes a machine learning-based method to classify the clustered pixels into coated and stripped areas.

2 METHODOLOGY

Figure 1 presents the workflow of the proposed system, which includes two parts: First, it demonstrates a low-cost illumination system to provide uniform diffuse lighting for the test samples to obtain high quality images; the second part includes a series of image processing methods to enhance contrast of the test images, reconstruct specular highlights, cluster pixels, and to classify these clusters. The image processing framework was developed using OpenCV 3.3.0 library (OpenCV 2017) in C++ Visual Studio Community 2015 platform. Details of these modules are discussed in the following subsections.

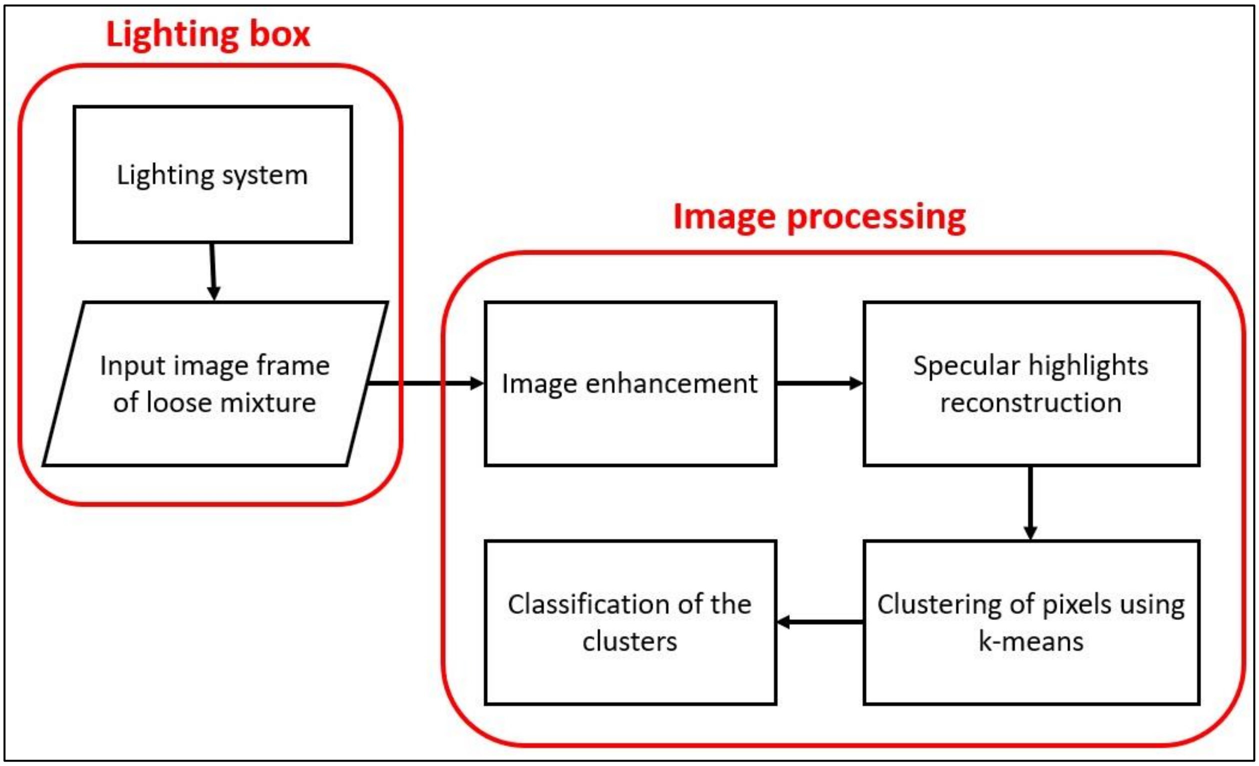

Figure 1. Workflow of the developed system

2.1 Lighting Box

Since specular highlights and shaded areas could be problematic in the classification stage, providing uniform indirect illumination could reduce these problems. Specular highlights are light reflections on the surface of the sample particles, which mainly occur on the coated surfaces, air bubbles, and water surface. Figure 2 provides two samples of excessive reflections in images captured under ambient room lighting. The top view of the beaker containing the sample is used to capture images as it usually provides the clearest view of the submerged test mixture. All the analysis will be carried out on this view and the retained percentage will be calculated based on this view.

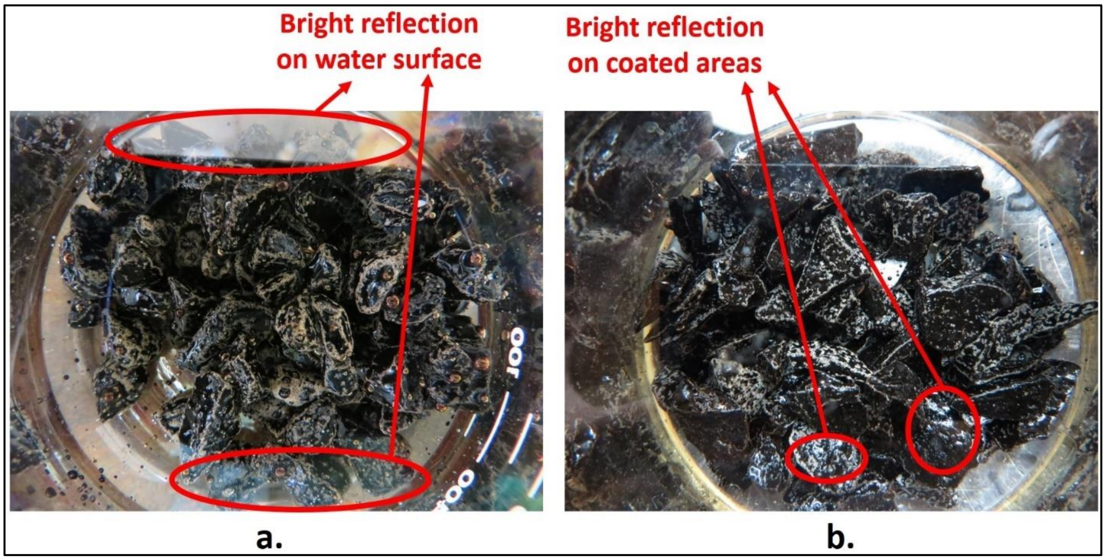

Figure 2. Specular highlights on a) surface of the water; b) coated areas

Images taken under ambient room lighting could have sever specular highlights and a bright reflection on the surface of water, which masks parts of the sample. In addition, shadows are imminent where direct lighting is provided from a certain direction(s). Therefore, an illumination box was developed to provide uniform and indirect lighting for capturing images from samples. This box is 20 × 20 × 20 cm to accommodate a 600 ml beaker containing test sample. The box was made of MDF boards with a white melamine surface bonded on the internal side. The White Melamine surface diffuses light arrays due to its uneven surface (Figure 3), which provides uniform lighting on the sample and reduces specular highlights and shadows. An LED string, which is attached inside an L-shaped piece, emits light toward the inner surfaces of the box which then diffused inward. The light intensity was measured using a lux meter in different spots within the box and the readings were consistent at 1214 lux. Details of this system is provided in Figure 3 and Figure 4 shows a prototype and sample image captured using this prototype.

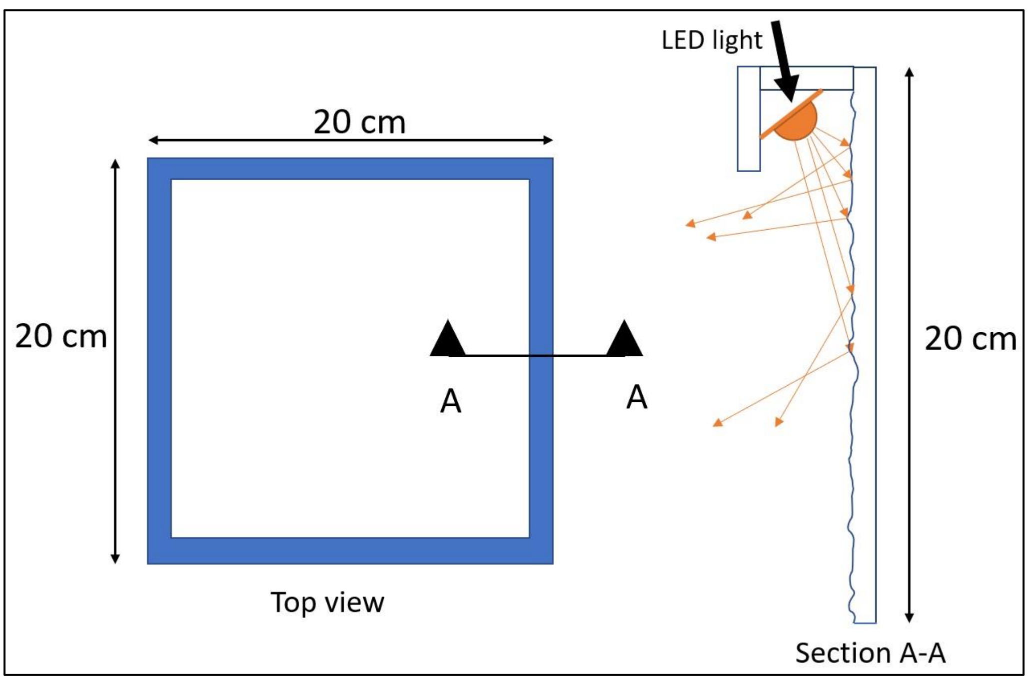

Figure 3. Details of the lightbox

a. b.

Figure 4. a) a lightbox prototype; b) sample image captured using this lightbox

2.2 Image Enhancement

Despite using the lightbox, captured images might still include low contrast and small specular highlights. Thus, a preprocessing module was developed to enhance contrast and remove specular highlights. Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to enhance the contrast in test images (Zuiderveld 1994), which facilitates distinguishing coated and stripped areas. Since this module aims at enhancement of the lighting of images, it firstly converts images to the L*a*b* colour space, because L* channel contains lightness intensities. The CLAHE method processes the L* (lightness) channel of the image and then the channels are merged again to create a new enhanced image. A sample of this process is shown in Figure 5.

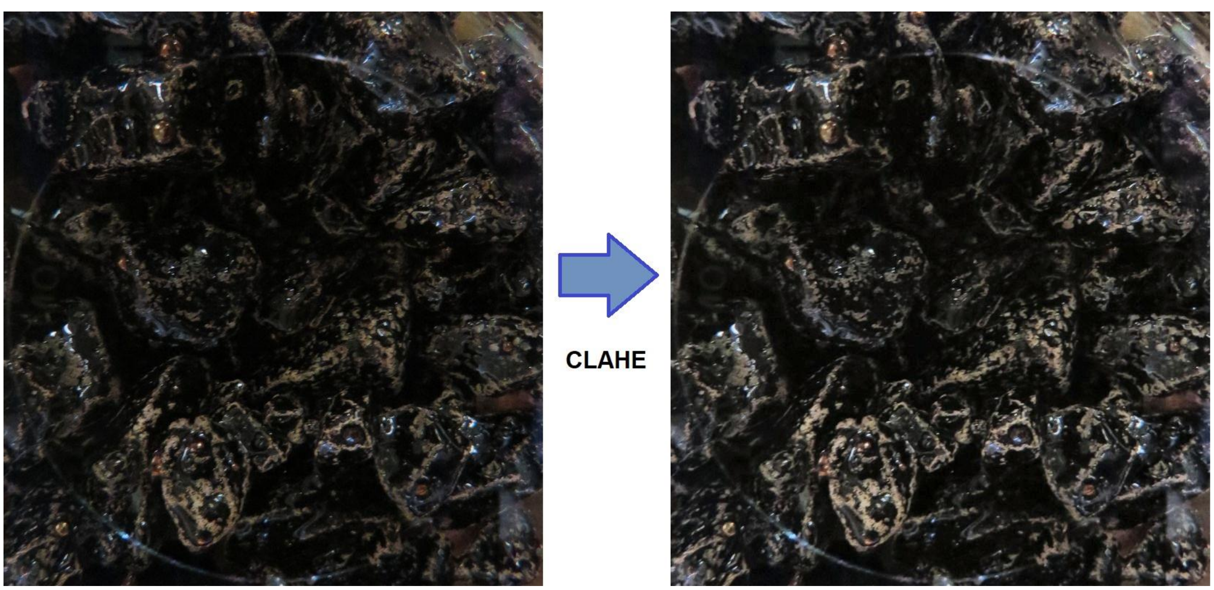

Figure 5. Sample contrast enhancement using CLAHE

The next process in this module corrects specular highlights. This method uses thresholding to isolate specular highlights in the L* channel of images (Figure 6.a), and then applies morphological dilation to widen the specular highlights to include their margins (Figure 6.b). Then an image inpainting method uses this mask to reconstruct the specular highlights (Figure 6.c). This inpainting algorithm initiates reconstruction process from the boundary pixels and gradually advances toward the inner regions of interest (Telea 2004). It calculates the intensity(s) of each pixel by normalizing the weighted sum of the known pixels around that pixel.

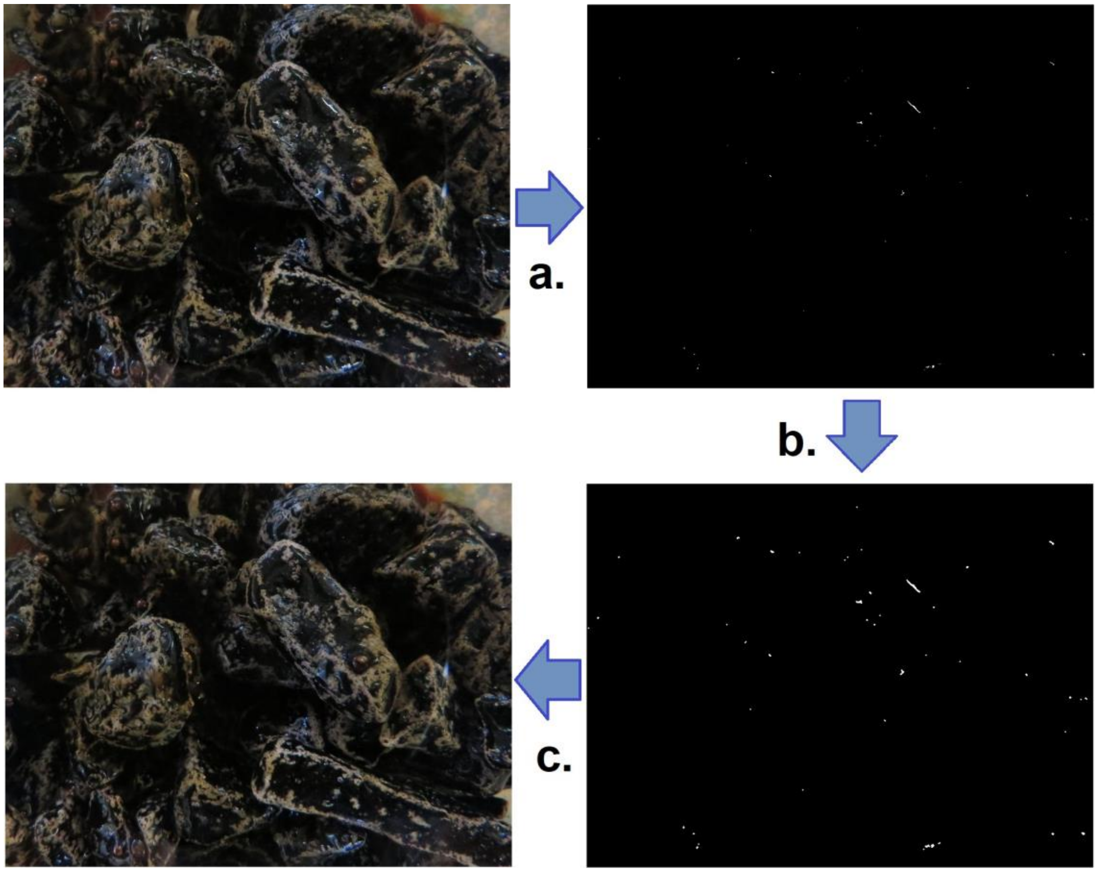

Figure 6. Reconstruction of specular highlights: a) thresholding on L* channel; b) dilating the mask; c) inpainting the masked regions in the original image

2.3 Clustering and Classification

K-means is used in this system to cluster the enhanced image. K-means segmentation aims at classifying n samples into k clusters, which is determined based on the distance of each sample to the clusters' mean. This method uses an iterative refinement approach, which initiates by assigning each sample to the cluster with the nearest mean and then updates the mean of the new cluster. This process continues until the assignments do not change.

Then these clusters should be classified to determine whether they represent a coated or a stripped region. Support Vector Machines (SVM) method with a linear kernel was used as a classifier in this system. Image histograms of the three channels of the regions were used as visual descriptors in training a classifier. A large number of histograms from positive and negative samples were used to train the SVM classifier. After clustering of the pixels by the k-means algorithm, this system calculates histograms of each cluster and passes them to the SVM classifier, which determines class membership (coated or stripped) of each cluster. Figure 7 shows the process of classification.

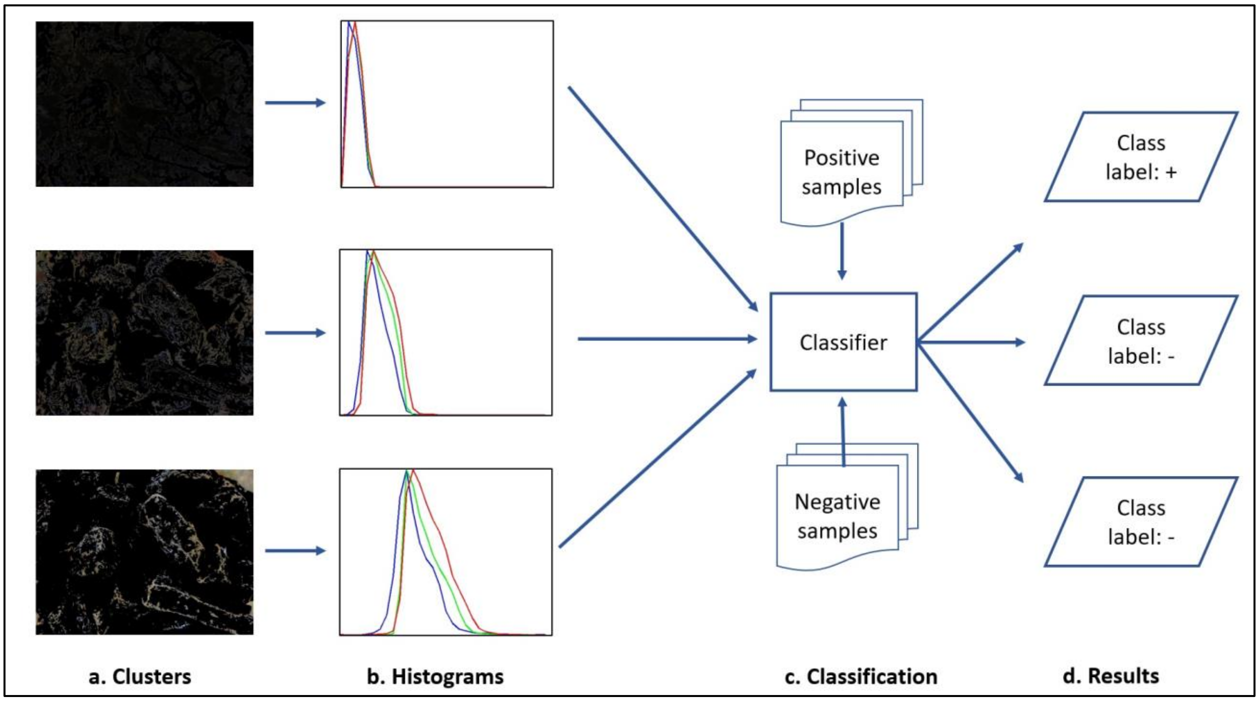

Figure 7. Classification process: a) clusters from k-means segmentation; b) histograms of blue, green, and red channels of each cluster; c) training of the classifier; d) classification outcome

3 EXPERIMENTAL RESULTS

The developed system was tested using three different configurations, including using three, four, and five clusters in k-means. Altogether, 73 samples mixtures were prepared according to the MTO's stripping by static immersion test (LS-285), which included different types of aggregate, such as dolomitic sandstone, granite-gneiss, and quartzite, and PG 58-28 asphalt cement.

All these samples were also assessed by expert technicians and the results were compared against the machine-measured results (retained %), and the absolute difference of the measurements for each sample was calculated. For example, if the retained coating percentages of a test sample were estimated at 75% and 80% in manual and machine assessments, respectively, the absolute difference would be 5%. Table 1 provides the summary of the results for the 73 images. Figure 8 illustrates a sample result of this process.

Table 1. Difference of the machine-measured and manual assessments in different combinations

Number of k-means clusters	Mean of the differences	Standard deviation of the differences
Three	3.22%	6.30%
Four	2.74%	5.04%
Five	2.85%	5.36%

Increasing the number of clusters from three to four improved segmentation of pixels and resulted in lower differences between manual and machine measurements. But the differences increased in the results with five classes in k-means process, which can be due to misclassification of some of the clusters. In some misclassified clusters, the histograms were marginal between positive and negative samples and the classifier could not correctly classify them.

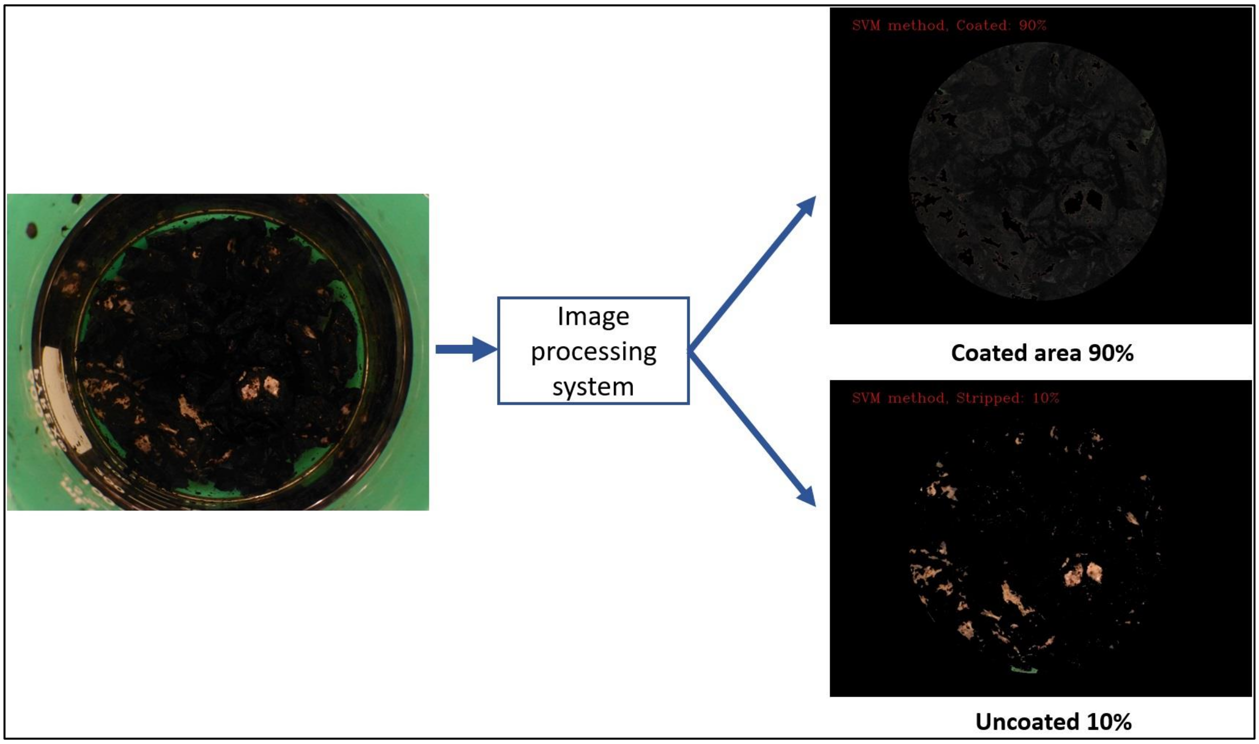

Figure 8. Sample result

Since the results in the configuration with four clusters showed the best outcome, these results were further analyzed in which the differences between the technician assessments and the results of the proposed system in different retained coating ranges were calculated (see Figure 9). Since the 65% retained coating is a critical threshold for pass/fail of an HMA mixture in this test procedure and the samples within the ranges of 65% to 84% and 50% to 64% had the highest level of differences (average difference of 8.85% and 5%), thus it is suggested that the samples measured by this system at 55% to 75% are doublechecked by an experienced technician.

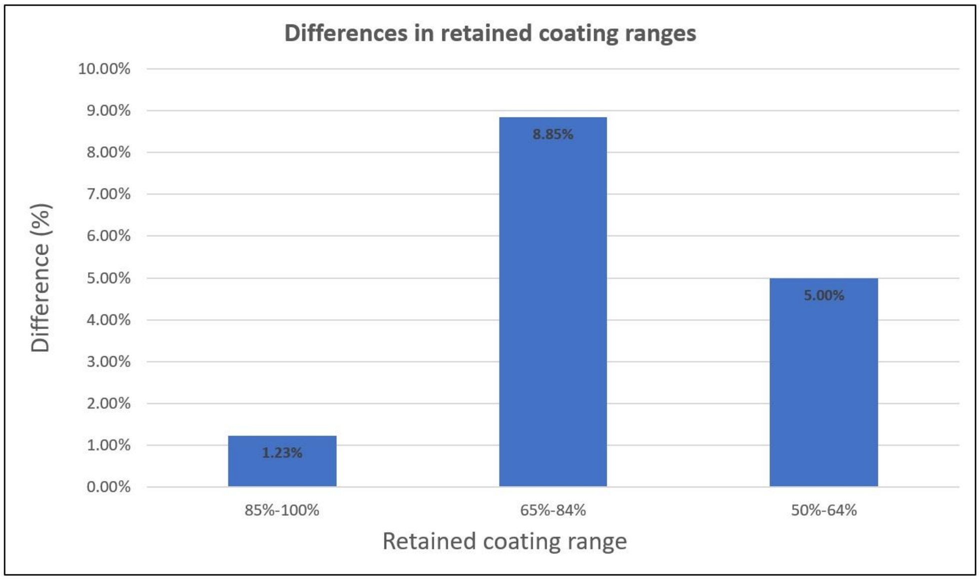

Figure 9. Differences between machine-measured and technician assessments in different coating ranges

4 CONCLUSION

A novel image processing system was proposed for automated stripping assessment of loose asphalt mixtures in MTO's static immersion test. In addition, a low-cost illumination box was developed to improve lighting of the samples. Experiments on a set of images from 73 samples showed an average of 2.74% difference between the machine-measured and manual assessments. This system demonstrated promising performance in estimation of the stripping of asphalt cement coating and has the potential to eliminate the subjectivity of manual assessments. Because two dimensional images are only used for assessment, a complete view of the mixture is not provided and therefore the result might not represent the entire condition of the test samples. Therefore, it is recommended to use images of multiple samples from the same mix design to address this issue. Moreover, assessment of the stained areas and removing dark shaded areas between aggregate particles are not fully investigated in this research project and future research will investigate methods to address these issues.

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