Object identification and visualization of urban road materials using narrowband near infrared imaging indexes

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Abstract : Classification performance analysis was done on selected narrowband near-infrared spectrum to identify urban road materials. There were five urban road materials to be identified; aggregate, asphalt, carbon organic, clay and concrete. The imaging indexes were selected that proposed a set of narrowband 760nm, 800nm, 850nm, 900nm, 950nm, 980nm with 720nm wide-band spectrum as normalization spectrum. Multilayer perceptron classification method was used. The result was presented where a significant classification performance shown on those five urban road materials with 76.6032 % using 10 fold cross validation on data data samples. A separate test data samples used for further predictions and visualization.

Keyword: **Imaging indexes, near-infrared, feature classifier, prediction and visualization, multilayer perceptron**

1.INTRODUCTION

The potential of urban road materials identification using near infrared vision system using the spectrum capability of common camera and optical filters had been proposed [1]. This research looked at common instrumentation with spectrum ranges from 350 nm to 1000nm that common to CCD and CMOS devices [2]. Upon further research, near infrared imaging indexes have difficulties to identify materials with content similarity like aggregate (sand, rock and gravel), clay and concrete have something in common, one of the material make-up is silicate based material.

Computer vision using multispectral imaging indexes

The novelty of this approach was the use of narrowband near infrared (NIR) multi-spectral to determine the imaging indexes and the additional UV/NIR classifiers. A red edge channel for improving land-use classification based on high resolution mufti-spectral satellite data was studied [3] which the interest was on 720nm onward of Near Infrared. The red edge is the discontinuation or transition between colour/from visible spectrum to infrared spectrum to infrared spectrum started at 720nm, a transitional spectrum ranges from visible to not visible to human eyes. As most of the remote sensing uses wideband spectrum channel, this study explored a set of narrowband imaging indexes for object identification.
The University of California at Santa Barbara [4] has analyzed Urban Area Covers with range of 350nm to 2500nm to record hyper spectral data of various urban material as shown the classification.
US Sandia National laboratory had a study on the usage of multispectral imaging indexes for autonomous ground vehicle navigation in 2003 as the early study of this subjects [5].

Multispectral infrared for urban materials analysis.

Infrared spectral analysis using spectroscopy and spectrometer looks at the distinctive shape and depth of spectral signature to analyse certain objects. The mixture of the material apply as well, such as for concrete. The process of concrete mixed cement, water, sand and other aggregate. This gave a variability of infrared spectral signature of the mixture [6]. Another approach used thermal infrared imaging (4500nm and above) to analyzing urban street surrounding material[7].
A visible ranges (400nm to 700nm) and near infrared (NIR) of 8 sensors were used to analyze the urban materials remote sensing using discriminant analysis. A feasibility study of 8 VIS-NIR sensors to discriminate urban materials [8].
The proposed approach used Near Infrared only as this has limited and minimal color variation and able to be done using relatively cheap camera and optical filters [9].

Initial development object detection sensor on road materials sensing using narrowband imaging indexes using SWIR (Short Wave Infra Red).

Narrowband Infrared object detection sensors had been proposed by Kosugi Laboratory at Tokyo Institute of technology [9]. The laboratory proposed using five normalized narrowband SWIR indexes for the experiments with five bands of 1100, 1200, 1300, 1500 and 1600 nm respectively, all in the SWIR region. The initial result was satisfactory to classify human skin, vegetation, animal/cloth, in which relatively high reflectance values were observed. While for inorganic matter such as car/ metal, concrete and asphalt were rather flat over the wavelength range spectrum profiles.
While adopting the same approach for different set of objects, the proposed approach differs from the usage of NIR instead of SWIR.

Urban road materials in near infra red (NIR) spectrum considerations

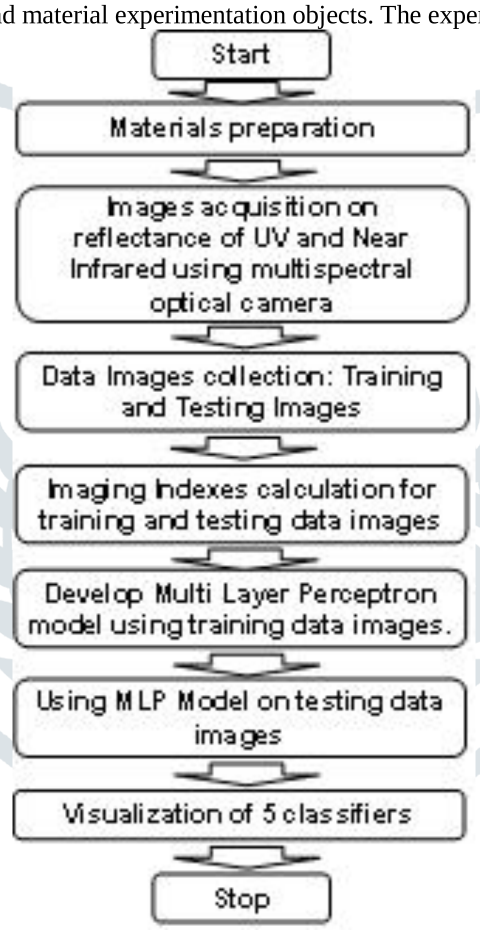
Aggregates are the main material make-up of concrete and road asphalt. It has a spectral signature at longer infrared waves, a thermal infrared region, at around 9000nm wavelength [10]. Aggregate and concrete differs on the presence of $CaCO_3$ (Calcium Carbonate) based on research on the present of soil properties on spectrum reflectance from UV up to SWIR (Short wave infrared) [11]. The study shows how the different composition of $CaCo_3$ effect on the spectrum patterns. Road asphalt did not have a signature spectrum characteristic in the range of 700nm - 1000nm, however, it had distinctly different spectrum plateau with

vegetation [12]. In the spectrum range of 700nm - 1000nm shown a comparison that it is distinctly different between road asphalt and concrete [13]. Another study looked at the various degree of asphalt removal on the asphalt road [14]. This happened during the asphalt road aging and deterioration. A study proposed an Exposed Aggregate Index of the asphalt-road [15] for that purpose.
Natural fibers from plants can be in the forms of shoots, roots and decomposition of plant material. In the spectrum infrared reflectance range of 700nm - 1000nm, the present of this organic carbon effects on the overall of soil spectrum characteristics [16].

Clay presents in soil along with aggregates and another mineral. Estimation of the present of clay and $CaCO_3$ suggested in the spectrum range of 2100nm to 2400nm [17], therefore it is more effective in SWIR region. However, another study of clay contains shows that there were minor variant spectral identified in the range of 700 - 1000nm [18]. The study focused on kaolinite clay where this is the abundance form found in soils in tropical area.
Concrete, as one of the component of urban road material, is a mix of several other materials. Concrete's near infrared pattern is influenced highly by aggregates and minor influence of the existence of limestone. Limestone ($CaCO_3$) has spectral variations at 1410nm, 870nm and 710nm [19]. The interested spectrum for this research was 870nm and 710nm.

2. RESEARCH METHOD

This was an initial attempt to visualize five urban road materials that common in the road environment using multi spectral narrowband near infrared computer vision. There are five urban road material categories used, those were asphalt-based silicate-based (code: Aggregate), Asphalt (code: Asphalt), Natural Dry Fiber (code: Carbon Organic), Clay (code: Clay) and cement-based materials (code: Concrete) as the urban road material experimentation objects. The experimentation approach is as in figure 1.



The detail steps were as follows:

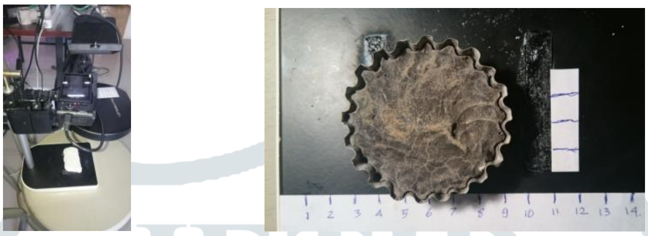
Step 1: Material Preparation.
The object for the classification training data for MLP development are seen in figure 2 below. There were 50 dry samples of five urban road materials categories with each sample where divided into 5x5 pixels area with total 8100 image blocks. That generated 405000 data-sets.
The sample categories used common objects on urban road materials with: 1.Aggregate samples; dry black sands, dry rocks and dry rock tiles, 2.Asphalt samples ; low quality bitumen coating, high quality bitumen coating and road asphalts, 3.Carbon Organic samples ; dry banana leaf, dry mango leaf and dry woods, 4.Clay samples ; building clay block, roof clay and clay tiles, 5.Concrete samples; lighter colored cements, darker colored cements and white buidling concrete blocks.

Figure 2 : From top to bottom. 10 variations of cement-based materials (Concrete), 10 sample variations of clay-based materials (Clay), 10 sample variations of silicate-based materials (Aggregate), 10 sample variations of natural dry fibers (Carbon Organic) and 10 sample variations of bitumen/asphalt-based materials (Asphalt).

Step 2: Images acquisition on reflectance of UV and Near Infrared using multispectral optical camera.

Multi-spectral optical filtered camera consists of two main parts: camera that capable to read 350 nm to 1000 nm light spectrum and optical filter rotating wheel as shown in figure 3(a). The rotating wheel consists (1) Low Pass UV filter (350nm up to 400nm), (2) No optical filter, (3) 720nm high pass optical filter (720nm to 1000nm), (4) 760nm with 10nm band pass optical filter, (5) 800nm with 10nm band pass optical filter, (6) 850nm with 10nm band pass optical filter, (7) 900nm with 10nm narrow band pass optical filter, (8) 950nm high pass optical filter to 1000nm, and (9) 950nm high pass optical filter to 1000nm. The choice of optical filters were different from earlier configuration [1], this was to accommodate the significant moisture left in the materials, even though those was dried, as same carbon organic material and concrete fore example as discussed earlier, capable to retain some moisture while asphalt based material were not. Those H2O effects on the 900nm to 1000nm ranges spectrum.

The camera were mounted and tightly bound to rotating wheel of optical filters replacing the common camera filter. Light source used a constant halogen lamp of 150 watt (in oppose of using sun light) to reduce the variability of light source light energy intensity. The camera was a mirrorless camera without UV/IR blocked filter as most of commercial camera pre-install with UV/IR blocking camera.



(a) (b)

Figure 3 : (a) Multispectral Camera with rotating wheel of optical filters and halogen lamp as standard light source. (b) Sample object.

Step 3: Data images collection: Training and Testing Images.

The arrangement of the data collection as shown in figure 3(b). There were 8100 data sets extracted from one sample that cropped into 450x450 pixels. Therefore it was 405000 data sets which divided into 70% for training and 30% for testing.

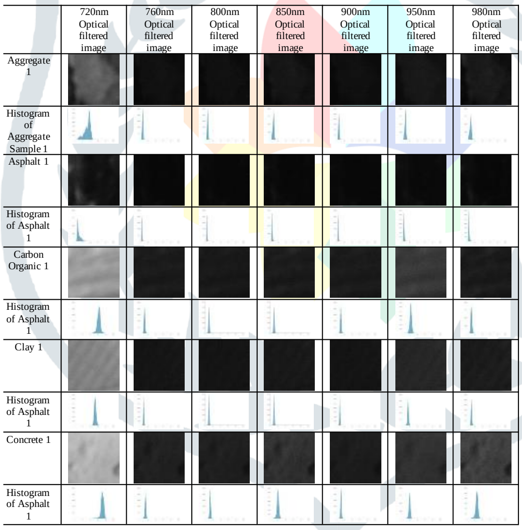


Figure 4: One sample image of each category for Aggregate, Asphalt, Carbon Organic, Clay and Concrete and its associated histogram analysis.

Step 4: Imaging Indexes calculation for training and testing data images.

Every spectrum reading was subjected to be normalized by 720nm spectrum from 720 nm high pass optical filter until up to 1000nm. Where 720nm is the transition point between visible to infrared spectrum as explained in the previous section. The choice of 720nm were to make the rest of spectrum normalized with the same spectrum ranges. The result was expected between -1 to 1. The formula were as follows:

$$II_{760nm} = \frac{(I_{720nm} - I_{760nm})}{(I_{720nm} + I_{760nm})} \quad (1) \qquad II_{800nm} = \frac{(I_{720nm} - I_{800nm})}{(I_{720nm} + I_{800nm})} \quad (2)$$

$$II_{850nm} = \frac{(I_{720nm} - I_{850nm})}{(I_{720nm} + I_{850nm})} \quad (3) \qquad II_{900nm} = \frac{(I_{720nm} - I_{900nm})}{(I_{720nm} + I_{900nm})} \quad (4)$$

$$II_{950nm} = \frac{(I_{720nm} - I_{950nm})}{(I_{720nm} + I_{950nm})} \quad (5) \qquad II_{950nm} = \frac{(I_{720nm} - I_{950nm})}{(I_{720nm} + I_{950nm})} \quad (6)$$

Step 5: Develop Multi Layer Perceptron model using training data images.

Multilayer perceptron were used as the model. The configuration was 500 iterations, learning rate 0.3 and momentum 0.2 with 10 fold cross validation. Those are common configuration that handle most of classification needs. The steps were to (1) extract the images into WEKA tabulation and (2) back to image from WEKA prediction into images. On the 405000 data sets, 70% was used as MLP modeland 30% for testing.

Step 6: Using MLP Model on testing data images.

The testing images data were cropped at 450 pixels by 450 pixels, and further calculated 5x5 pixels average. This was to reduce the computational resources needed. There were testing 15 samples (30% of all objects) as described earlier. The data sets for each object were 8100 (90 pixels by 90 pixels).

Step 7: Visualization of 5 classifiers.

All 15 (30%) samples were visualized to give the idea of the performance of the proposed classification methods, not only based on the confusion matrix as well.

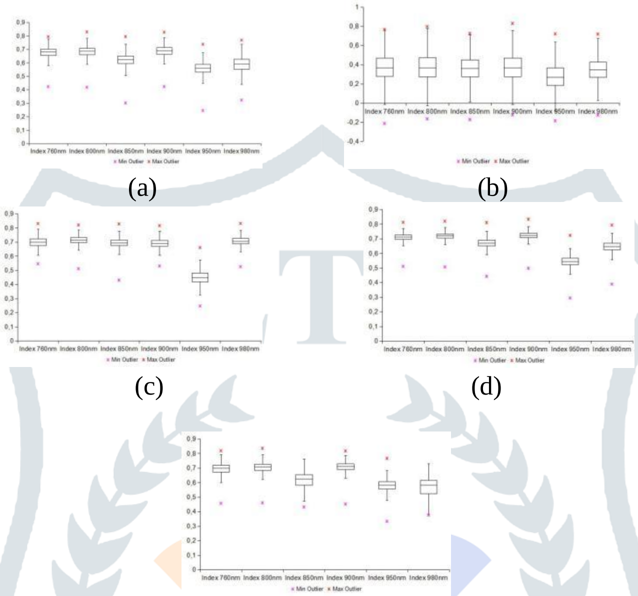
3. RESULT AND ANALYSIS

This section consists of three main parts: data analysis using box-plots, near infrared predictors and results.

There were two ways to show the performance of the classification: (1) Confusion matrices, as the performance classification of the MLP model, (2) visualization on different sets of data using the MLP model to illustrate the results.

3.1.Box-plot data analysis

The calculation of imaging indexes, formula 2 to 8, were visualized using box-plot as shown in figure 5.



(a) (b) (c) (d) (e)

Figure 5. Box-plots of all imaging indexes, 760nm, 800nm, 850nm, 900nm, 950nm, 980nmfor all material categories.(a) Aggregate, (b) Asphalt, (c) Carbon Organic, (d) Clay and (e) Concrete

Those box-plots shows the potential of the proposed method and system for classification of five urban road materials. The notable different was asphalt around 0.4 while the rest were hovering around 0.5 to 0.7. Another notable different were the indexes of 900nm, 950nm and 980nm where H20 effects located.

3.2. Near infrared classifiers Model on Training Data

The data were split for training and test data into 70%-30%, with following results for five urban road materials classification in table 3 forMLP model.

Table 3: Confusion matrices for near infrared

	Aggregate	Asphalt	CarbonOrganic	Clay	Concrete
Aggregate	35.024	2.925	213	8.881	9.657
Asphalt	3.644	52.111	10	22	913
CarbonOrganic	193	1	53.724	2.781	1
Clay	5.545	104	3.538	42.899	4.614
Concrete	16.667	565	8	6.048	33.412

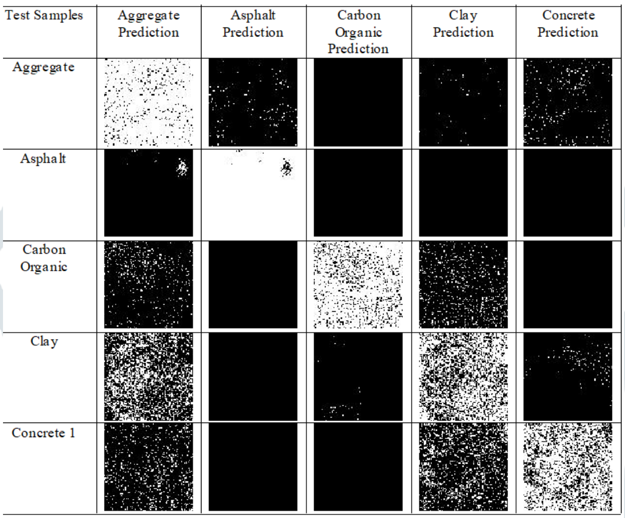
3.3. Near infrared prediction on Testing Data

Those 15 testing (30% of 50 objects) data images as described in the previous section were subjected to the MLP model trained earlier with the prediction confusion matrix the visualization as in table 4 on the testing data.

Table 4: (a) Confusion matrix and (b) visualization table for near infrared predictors

Actual \ Prediction	Aggregate	Asphalt	CarbonOrganic	Clay	Concrete
Aggregate	21134	295	106	1894	871
Asphalt	2138	22112	22	4	24
CarbonOrganic	500	-	23079	721	-
Clay	6547	31	1878	15016	826
Concrete	3862	-	-	2621	17817

(a)



(b)

Both confusion matrices and visualization of separate testing data shows the relative performance of prediction on those five material categories.

4.CONCLUSION

This initial NIR imaging indexes shown the potential in predict the dry material categories of aggregate, asphalt, carbon organic, clay and concrete from the common objects found in urban road materials such as dry black sands, dry rocks and dry rock tiles; low quality bitumen coating, high quality bitumen coating and road asphalts; dry banana leaf, dry mango leaf and dry woods; building clay brick, roof clay and clay tiles; whiter cement, grey cements and white building concrete brick.

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