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Urban Road Materials Identification using Narrow Near Infrared Vision System

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ABSTRACT

An urban road materials vision system using narrow band near infrared imaging indexes were proposed. This proposed imaging indexes were enhancement for previous work on autonomous multispectral road sensing method. Each urban road material has different near infrared spectral patterns which is as the base of its spectral identification. The new proposed imaging indexes, which using similar formula of NDVI, was normalized with narrow band near infrared spectrum range of 720nm to 1000nm of wavelength, were used to identify concretes, aggregates/sands/rocks, clay, natural dry fibers and bitumen/asphalt that make up most of urban road materials. This paper proposes imaging indexes evaluation from experiment results to identify those urban road materials. There were seven narrow band optical filter sets with the center spectrum at 710nm, 730nm, 750nm, 800nm, 870nm, 905nm and 970nm. Normalization band used was 720nm using high pass optical filter. The proposed multi-spectral imaging indexes were able to show the potential to classify the selected urban road materials, another approach may need to clearly distinguish between concrete and aggregates. The comparison to the previous imaging indexes (NDVI, NDGR, NDBR) were presented that used for urban road materials identification.

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1. INTRODUCTION

Current autonomous vehicle vision system was focused on LIDAR and color-based vision system by literature review by Rosenzweig in 2015 [1]. LIDAR was basically distance information, while color based vision system used the techniques that mimic the understanding of human perception of the environment. Hyper spectral infrared spectroscopy offers the possibility in identifying the material make up on the road scene by analyzing the hyper spectral data [2], however, this is a computationally intensive approach. Early feasibility study by using imaging indexes had been assessed as early as 2003 [3]. The finding concluded that it was not sufficient to use the existing indexes that available in that time, to achieve the intended purpose. More indexes development is needed to enhance the feasibility for road material identification using imaging indexes. Therefore, this research focused on the enhancement of imaging indexes by introducing selected narrow infrared bands to overcome the shortcoming of current available imaging indexes.

After the Fogler's feasibility report in 2003, there had not been any significant imaging index development for urban road material reported. The most successful imaging index, by far, was NDVI (Normalized Difference Vegetation Index) for various of uses. Where the following development of other indexes follow the same path using two or more wide spectra bands of visual range (400nm to 700nm) and infrared region, and these were used as well in Fogler's feasibility study in classifying urban road materials for autonomous vehicle purpose. However, those were imaging indexes using wide spectral bands, red, green, blue and the entire near infrared band.. The first narrow band imaging index were proposed in 2010, for the purpose of road safety, where the goal was to distinguish human skin, cloth and animal from other objects in front of vehicle [4]. The research proposed that SWIR (Short Wave Infrared) were suitable to identify, with focus on, human skin. The approach was to sample of narrow bands of 1100nm, 1200nm, 1300nm, 1500nm, 1600nm and develop associated 5 indexes to form a decision tree to distinguish the main object, human skin, from the rest. While this was successful on the objective to distinguish human skin on the road scene, however, it was less successful for other objects, such as, animal/clothes. Another note is that the choice of the selected narrow bands were not taken into account the characteristic of transmittance or absorbent infrared spectra of the material being observed.

1.1. Hyper spectral Imaging Spectroscopy, remote sensing and Imaging indexes

Most of urban and road network remote sensing used image processing methods on color images, like recent approach using clustering algorithm combined with hill climbing for classification of remote sensing image [5]. Another example of current color-based computer vision approach of material identification and classification were used texture-based information [6], [7].

Some works on hyper-spectral imaging spectroscopy and remote sensing data in urban road materials imaging spectroscopy were available. An early library of hyper-spectral data of urban landscape materials had been built [2]. Categorization of urban landscape materials that relate to hyper spectral remote sensing were proposed. Furthermore, the approach was used to assess the road condition (asphalt road) for the aging and deterioration using the observation of various asphalt road condition hyper-spectral data [8], [9].

Other material that common to urban landscape material were clay that as part of soil-mix and calcium carbonate that as part of concrete mix, a study of the comparison of hyper-spectral data both in laboratory and airborne sensing is available [10]. Soil is another aspect of urban landscape, hyper spectral data of water presence in soil was collected [11]. The observation was that the longer the infrared wavelength, the stronger the effect of water spectra in the overall soil - water mix. Therefore, shorter infrared region was not impacted much by the water presence in comparison with longer infrared wave. Another research [12] added the road classification not only based on asphalt, but gravel and concretes on his hyper spectral-data collection and analysis. While early comparison used Pavement Condition Index (PCI) and Structure Index (SI) was available, other comparison that based on Exposed Aggregate Index (EAI), Munsel Grey Scale and Degree of asphalt percentage with the Hyper spectral data analysis were proposed [13], [14].

1.2. Proposed Imaging Indexes for Urban Road Materials

The purpose of this multi-spectral urban road material vision system is to identify urban road materials by imaging indexes, in the range of 700nm to 1000nm, for five dry urban road materials: clay, aggregates, natural fiber, concretes and asphalts. An early attempt of multispectral remote sensing had classify those urban road material as shown in table 1, this is the base of the mapping of four material group from the library of spectral dimension for Urban Area Covers using AVIRIS data by the University of California at Santa Barbara [15]. This library used Analytical Spectral Devices (ASD) field spectrometer with range of 350nm to 2500nm to record hyper spectral data of various urban material as shown the classification in Table 1.

Table 1. University of California at Santa Barbara's urban material classification

Level 1	Level 2	Level 3	ID
Built Up	Building/Roofs	Light-Gray Asphalt Roof	1
		Red Tile Roof	2
		Wood Shingle Roof	3
		Red-gray Tar Roof	4
		Red-gray Tar Roof (New)	5
		Red-gray Tar Roof (Old)	6
		Ligh-Gray Metal Roof	7
		Green-gray Metal Roof	7
	Trasnportation Area	Concrete Road	8
		Light Asphalt Road	9
		Dark Asphalt Road	10
		Parking Lots	11
		Railroad Tracks	12
	Other built up covers	Tennis Court	13
		Sport Field Tartan	14
Vegetation	Green Natural/Quasi natural Vegetation	Bushes	15
		Grass Land	15
		Forest	15
	Green Agricultural Vegetation		15
	Green Urban Vegetation	Trees	15
		Residential Grass Land	
		Golf Course Grass Lands	16
	Non-Photosynthetic Vegetation (NPV)		17
Non Urban or non vegetated bare land surface	Bare Soil		18
Water Bodies	Natural / quasi natural water bodies		19
	Swimming Pools		20

The early attempt to simplify the identification of vegetation areas and its surrounding condition was the use of NDVI (Normalized Vegetation Index). It was used to identify vegetation or not of the Great Plains study back in 1973 [15]. Later, this approach were used and developed further by Compton Tucker of NASA's Goddard Space Flight into series of journals of the usage of NDVI in the launch of ERTS-1 (Landsat-1) which is calculated as follow :

$$NDVI = {(NIR - Vis)} \Big/ {(NIR + Vis)} \tag{1}$$

Where NIR is Near Infra Red band and VIS is the Visible Spectrum Band, where most of the implementation uses red band light spectrum for the visual band. This normalized approach will give the range of value from -1 to 1.

Similar to NDVI formula was the base of this research that look at the possibility of developing a set of imaging indexes in the near infra red range from 700nm to 1000nm to identify specific materials, in this case urban road materials. The urban road materials were set to clay, aggregates (sands and rocks), concretes, dry natural fiber (leaves and woods) and asphalt/bituminous material as the common make-up of road materials and its surrounding environment. Vegetation, which is part of road surrounding, was not considered in this scope, as NDVI has been around for this purpose since back in the 70s.

Concrete, as one of the component of urban road material, is a mix of several other materials. A typical concrete may take 10 to 15 percent of cement, 60 to 75 percent aggregates, 15 to 20 percent of water and 5 to 8 percent existence of air. Limestone, or known as calcium carbonate substance ($CaCO_3$), has a important hydration role of the cement along with other minerals [16]. Therefore, cement's near infrared pattern is influenced highly by aggregates and minor influence of the existence of limestone. Limestone ($CaCO_3$) has distinct spectral at 1410nm, 870nm and 710nm [17]. The interested spectrum for this research was 870nm and 710nm, as this is within near infrared spectrum with the range of 700 - 1000nm as the limitation of camera used..

Road asphalt did not have a signature spectrum characteristics in the range of 700nm - 1000nm, however, it had distinctly different spectrum plateau with vegetation [9]. In the spectrum range of 700nm - 1000nm shown a comparison that it was distinctly different between road asphalt and concrete. Another study looked at the various degree of asphalt removal on the asphalt road [13], [18]. This happened during the asphalt road aging and deterioration. Asphalt materials on the road will diminish and exposing further the aggregates/gravels. This study shows that once the asphalt material removed, the spectrum characteristic of the range 400nm - 1000nm close to gravel's spectrum characteristics as more gravel/aggregates exposed out. This study proposed an Exposed Aggregate Index of the asphalt-road [14] for comparison.

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 [19]. As it has mentioned in the previous paragraph, it has similar characteristic in between asphalt and concrete.

Clay presents in soil along with aggregates and other minerals. Estimation of the present of clay and $CaCO_3$ suggested was in the spectrum range of 2100nm to 2400nm [20]. However, another study of clay contain shows that there are various spectral possible for identification in the range of 700-1000nm [21]. The study focused on kaolinite clay where this is a the abundance form found in soils in tropical area.

Natural fibers from plants has significant portion of total organic carbon in soil [22]. It 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 [23]. Soil, as in the argument as part of road surrounding material, where not included as this identification due to the fact that it mainly consists of sands, clay and silt. Where the main contributor of silt is carbon material from vegetation natural fibers that noticeable from the infra red imaging [24]. A study was conducted in looking at different ingredients of organic carbon, clay and sands/aggregates in showing variation of the spectral characteristics range from 500nm to 2500nm [25]. A comparison of spectral infrared range 700nm - 1000nm were shown for organic only, low organic with high level clay and low organic carbon with high level of sand/aggregates.

Water content in soil changes the infrared spectrum characteristics of soil [11]. Therefore, this initial research only concern with dry materials of clay, aggregates, concretes, asphalt and natural plant fibers. Other study shows the infrared spectral variation with the present of decomposed vegetation, vegetation and moist soil [26]. This finding enforces further the effect of water content on the variation of near infra red spectral characteristics.

2. RESEARCH METHOD

This research consists into two parts, (1) the design of research instrumentation and imaging indexes selection and (2) experimentation tests and analysis.

The objective of the first part was to develop nine set of cameras and optical filters to support the identification of five dry materials: clay, aggregates, natural fiber, concretes and asphalts. The ranges of near infra red spectrum under this study was from 700nm to 1000nm. The selection of 1000nm as the cut-off spectrum is due to the CMOS/CCD camera's spectrum limitation [27]. The nine cameras were one RGB camera and nine Infrared cameras.

The selected optical filters specification was important aspect in this research. There were two aspects that needs to considers on the selection of the optical filters: spectral center and Full Width at Half Maximum (FWHM). The selected optical filters covers the sample ranges of 700nm to 1000nm that available in the market are as follows:

1. UV/IR cut optical filter for RGB camera to ensure that no UV or IR interfere the image result
2. 720nm high pass optical filter, this is used as the normalized spectrum band
3. Narrow-band optical filter with center at 710nm and FWHM 10nm.
4. Narrow-band optical filter with center at 730nm and FWHM 10nm
5. Narrow-band optical filter with center at 750nm and FWHM 40nm.
6. Narrow-band optical filter with center at 800nm and FWHM 10nm.
7. Narrow-band optical filter with center at 870nm and FWHM 10nm
8. Narrow-band optical filter with center at 905nm and FWHM 10nm
9. 950nm high pass optical filter which will be cut off the camera at 1000nm

The light source used Halogen Lamp with 250 watt. The halogen lamp used due to the wide range of infrared spectrum that resembling the solar radiation spectrum as shown in Figure 1. This Figure 1 shows that sunlight is disturbed by the present of water vapor at the atmosphere. Therefore, due to this variability, the fixed 250 watt halogen lamp source were used, not sunlight as the source of light.

There are other environment variables were fixed: room temperature at 27-28C and room humidity at 80%. As the content of water in the material were out of the scope of the experiment, the materials subjected for this experiment were dry materials with the standard treatment of at least three hours of exposure to the halogen lamps. The research instrumentation shown in the Figure 2.

The instrumentation were connected to a PC where MATLAB used for image acquisition and where the average value sampling area (15 by 15 pixels) calculated. Further analysis used MS Excel for tabulation and box-plot presentation.

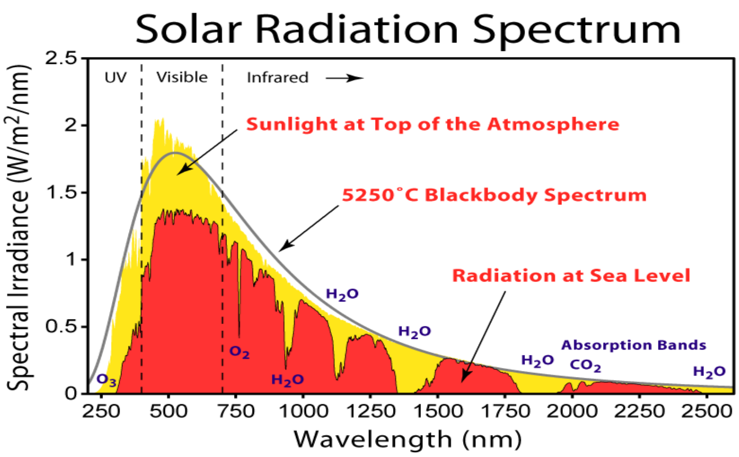

Figure 1. Solar radiation spectrum. This Figure was prepared by Robert A. Rohde as part of the Global Warming Art project (http://www.globalwarmingart.com/)

The second part was on the experimentation test, and analysis method. The experimentation method was as follows:

1. Every material object was placed in the two middle boxes at the template
2. Image is taken at 15 x 15 pixels at the center of the box. This is a gray level image, except the one RGB camera at the center (Figure 1) right

3. Average gray intensity pixels value were calculated and recorded.
4. 10 samples per category (Clay, Aggregates, Natural Fiber, Concretes at various color & types and asphalt at various quality

At this stage, the experiments used 5 material categories, 10 samples each, 3 different form/shapes. Example for aggregates were in the form of sands, rocks and rock tiles.

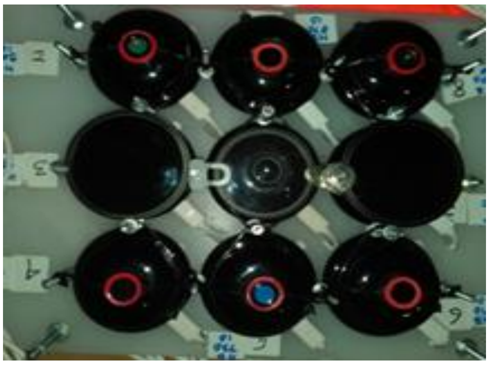

Figure 2. On the left is the instrumentation setting and on the right is nine cameras and its associated optical filters

The analysis method is as follows:

1. Near infra red imaging indexes with normalization (N) value from 720nm high pass optical filter for the rest of NIR optical filters (V) value using the following index calculation, similar to formula (1)

$$I = {(N - V)}/{(N + V)} \tag{2}$$

It will be only in the range of -1 to 1.

2. The seven indexes were associated with optical filter number 3 to 9 in the section 2 in the third paragraph. These seven indexes were calculated for every image taken. This is shown in section 3.1.
3. Box-plot calculation value for each material category for all 10 samples was collected to visualize the patterns for each material category.

For result comparison, the same data aquisition was calculated using imaging indexes (NDVI – Normal Difference Vegetation Index, NDGR - Normal Difference Green-Red and Normal Difference Blue-Red as stated in the Fogler's Report [25].

3. RESULTS AND ANALYSIS

In this section, the results of method explained in the previous section for five urban road material categories are presented and analyzed. The seven indexes were calculated and presented using box-plot approach. The data collected was calculated using NDVI, NDGR and NDBR as comparison.

3.1. Experimentation Results

The categories are presented as follows: dry natural fibers/leaves, asphalt/bitumen, concretes, aggregates, and clay. The next Figures visualize the pattern of each category. The horizontal axis presents the 7 proposed imaging indexes using 7 narrow band of 710nm, 730nm, 750nm, 800nm, 870nm, 905nm and 970nm.

Across five categories, index no 6 was not a good candidate for classifier overlap across five materials. Therefore, optical filter of 905nm with FWHM 10nm were not suitable for classifying dry natural fiber, concrete, asphalt/bitumen and aggregates without additional parameter.

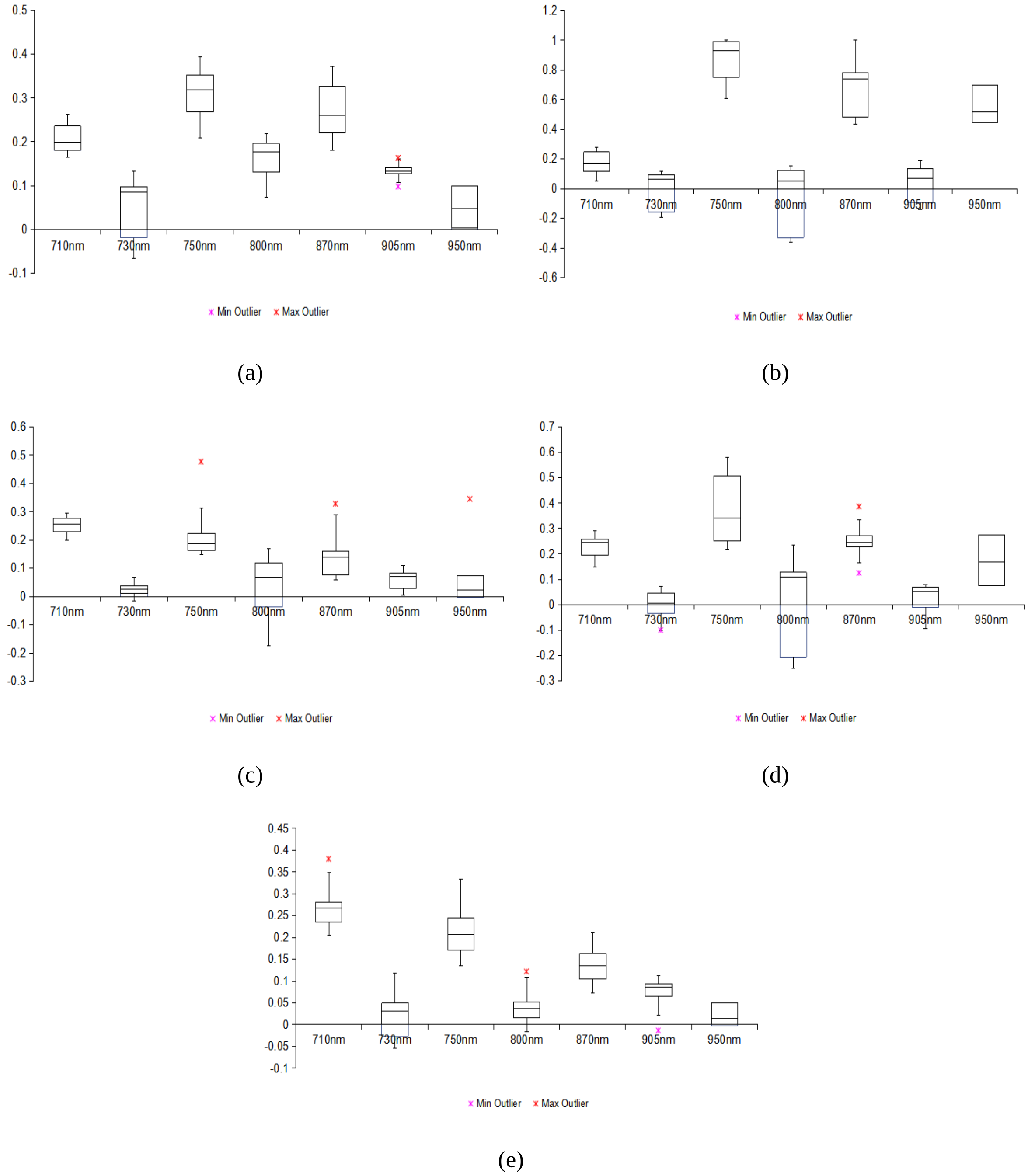

Figure 4. (a) Dry Natural Fibers/Leaves of all 7 proposed imaging indexes, (b) Asphalt/Bitumen of all 7 proposed imaging indexes,(c) Concretes of all 7 proposed imaging indexes, (d) Aggregates of all 7 indexes, (e) Clay of all 7 indexes

3.2. Comparison Analysis.

As comparison, the following graphs use the current approach that using wide bands for the indexes. For example, NDVI, this index use Red Channel and an entire NIR band. The imaging indexes (NDVI, NDGR and NDBR) used for classification of urban road material used for autonomous vehicle [3]. There are other visual spectra bands, Green and Blue that used as well. Therefore, given the same sample material that has RGB information as well, the box-plots for NDVI, NDGR and NDBR is presented in Figure 5.

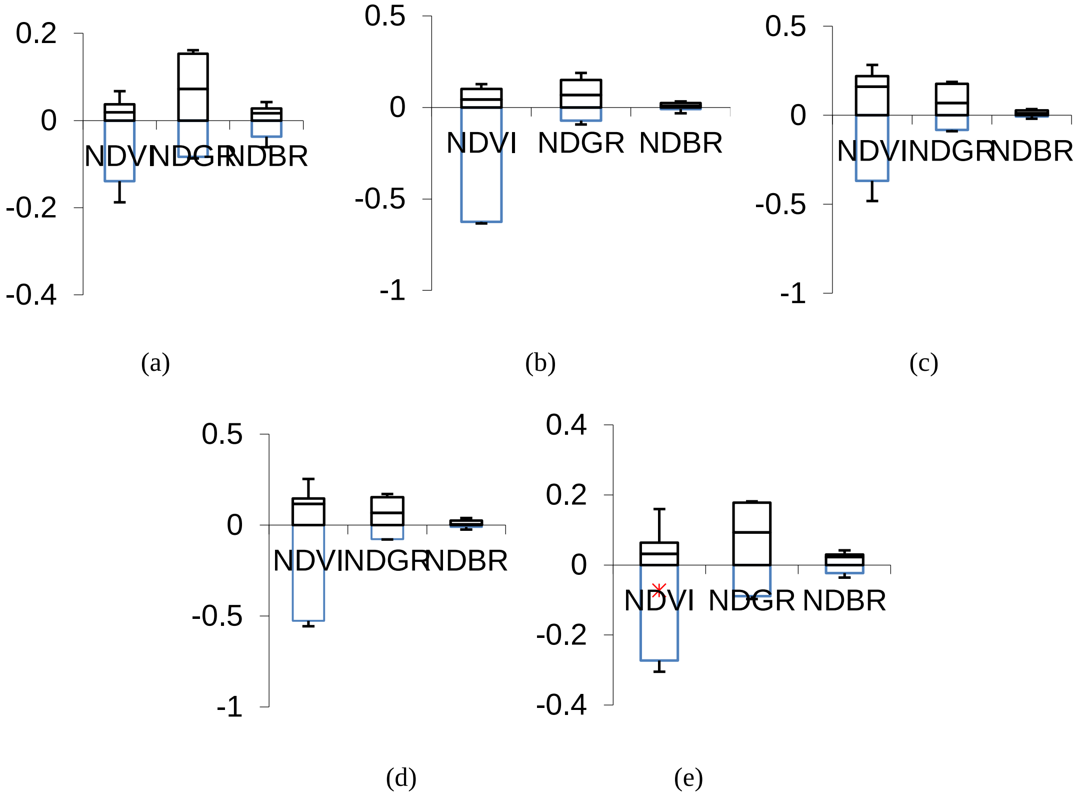

Figure 5: (a) Dry Natural Fibers/Leaves of all 3 previous imaging indexes, (b) Asphalt/Bitumen of all 3 previous imaging indexes, (c) Concretes of all 3 previous imaging indexes, (d) Aggregates of all 3 previous imaging indexes, (e) Clay of all 3 previous imaging indexes

3.3. Analysis.

In section 3.2. for wide band and color-based imaging indexes, it was obvious that the box-plot Figures shows for all 5 material categories are overlapping. This is due to, in short distance, the color variation were influencing on the index calculation from the various degree of color in the same material category. In remote sensing application, this was minor influence, due to averaging and blurring effect of image over such long distance. For example, the concrete samples were vary with different type of cement; white and gray cement. While in infrared region, the color information were not having any impact.

In the section 3.1. for narrow band and infrared only imaging indexes. Other than index no 6, there were analysis result of section 3.2. comparison for the rest of indexes and for all five categories:

1. Asphalt/Bitumen and concrete & aggregate were clear distinguishable
2. Concrete and.aggregate were indistinguishable, therefore it may need to find another index or index(es)
3. Clay and aggregate/concrete were different value ranges but close
4. Natural fiber and Asphalt/bitumen were clearly distinguishable
5. Natural fiber and concrete/aggregate were overlapped except on the index 1 and index 5
6. Natural fiber and clay are mostly overlapped at index 2 and 3, minor overlapped at index 1 and 7, distinguishable at index 4.

The objective to identify the five urban road materials was yet met, as aggregate and concrete were difficult to distinguish. Another index need to be proposed to distinguish these two important urban road materials, as both the urban road materials have different material hardness that important for vision system for car comfortable driving. While this shows potential that narrow band and infrared only imaging index shows its potential, however, the next step need to be taken is to find the appropriate classifying methods that used the combination of those 7 imaging indexes.

4. CONCLUSION

The proposed multi-spectral vision system to identify urban road materials by imaging indexes has been proposed. Spectrum center at 905nm was not a good imaging index candidate as there was an overlapping results across five material categories. There are six findings that potential for further classification method or visualization. However, another index or index(es) need to be proposed to clearly distinguish between concrete and aggregate.

In comparison with previous imaging indexes (NDVI, NDGR and NDBR), a collection of narrow band and infrared only imaging indexes was superior. Therefore, this research added the feasibility of using imaging indexes for urban road materials identification.

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