

Soil Property Characterization by Image Acquisition in Unmanned Construction Systems

Ritsumeikan University

Student member

○Shwetha Shivanna

Ritsumeikan University

Fellow member

Takaaki Yokoyama

Ritsumeikan University

Fellow member

Kazuyoshi Tateyama

1. Introduction

Soil property is one of the key factors determining soil trafficability which in turn affects vehicle mobility in construction sites. Construction sites in muddy areas or rough terrains make it increasingly difficult for movement of heavy machinery thus reducing its performance efficiency. Thus, an understanding of the soil characteristics in real time may help the operator of the machinery better assess the surrounding conditions. To give an example, it may be difficult to evaluate the geotechnical information of the field and the area around the construction machine. If an imaging technique can be developed for easy retrieval of basic information like color, texture, moisture content etc., it may be possible to avoid soft ground or difficult ground conditions. Therefore, soil characterization becomes important in the context of unmanned construction practices.

2. Materials and test methods

Decomposed granite soil, commonly referred to as Masado was used for the experimental study. Grain size distribution was carried out by hand sieving as per JIS A1204 standards (Fig. 1). The soil had particle size diameter falling under 2mm and grain size analysis revealed a well graded sample set and categorized as sandy loam. Soil color is one of the easily distinguishable factors and by visual observation falling in the Munsell color soil hue range of 7.5YR– 10YR.

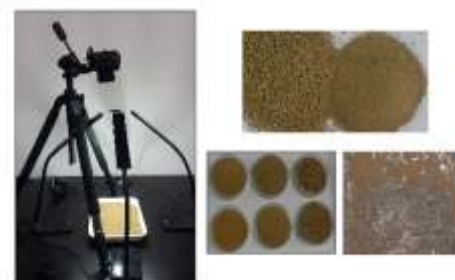


Figure 1: Soil samples and experimental set up

3. Experimental set up and methodology

Soil sample was placed in a flat basin and height of sample was 40mm. Water was mixed in varying degrees to simulate site conditions (Fig. 2). Soil images were acquired using a Nikon D7100 Single Lens Reflex digital camera. The camera was mounted on a tripod with the camera lens facing the surface of soil sample at a distance of 0.5m (Fig. 1., Ref. 1). The experiment was conducted in a dark room with only LED as a light source to maintain uniformity and standardize the procedures. The digital images having a resolution of 6000 x 4000 pixels was stored in RAW format. Images were then converted to software readable image formats and cropped to have a ROI (regions of interest) of 2000 x 1000 pixels for use in image analysis. At first, the dry and wet soil images were analyzed in CIE $L^*a^*b^*$ color space and the pixel value range was studied in order to establish the correlation between the two parameters (Fig. 3). Next, edge detection and texture segmentation analysis were carried out.

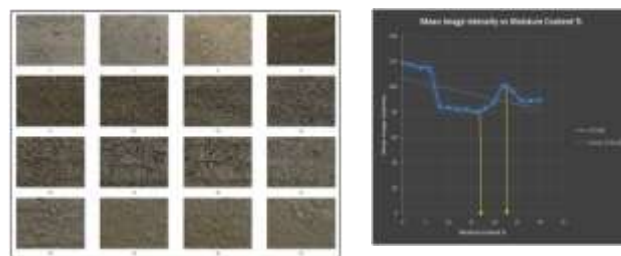


Figure 2: Color and image intensity change with soil moisture variation

4. Results and Discussion

Soil moisture inversely influences the image intensity and pixel count in the image. Wet soil was distinguished by noting the b^* values in $CIE\ L^*a^*b^*$ color space, which decreased significantly when water content in soil increased (Table 1). Due to visible change in soil color, color thresholding was used to differentiate wet and dry parts in a soil image. But this was limited to the type of camera sensor and lighting conditions being constant. Edge detection clearly identified the soil particles by detecting the grain edges, which allows for simple soil classification as sandy, silty or clayey. Further, by using appropriate texture segmentation algorithm (Fig.4), the areas with water on the surface could be distinguished, due to the reflectance of light from the water surface which created a glossy effect. Thus, the parts of the image in which the soil was either saturated with water (black area) or surface wet (white area with undulations) could be identified.

4. Conclusion

Although this study is limited by the type of digital camera used, if the geographical profile of an area is known, the imaging technique can prove useful to assess the ground conditions in real time. Further studies involve building of soil datasets for creating soil classification models specific to construction zones.

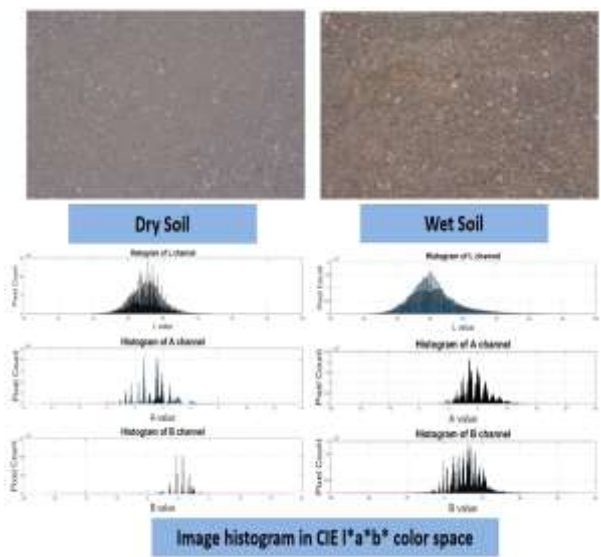


Figure 3: Color histogram for dry and wet soil in $CIE\ L^*a^*b^*$

Table 1: Values for a^* and b^* for dry and wet soil

	1-Dry soil			2-Wet soil		
	Pixel Count	Value range	Peak value	Pixel Count	Value range	Peak value
A Channel(a^*)	4.34x10 ⁶	0 to 6.5	3.36	3.58x10 ⁶	-0.2 to 12	-3.5
B Channel(b^*)	10.4x10 ⁶	-3.5 to 4	0.64	2.6x10 ⁶	-7 to 20	9.7

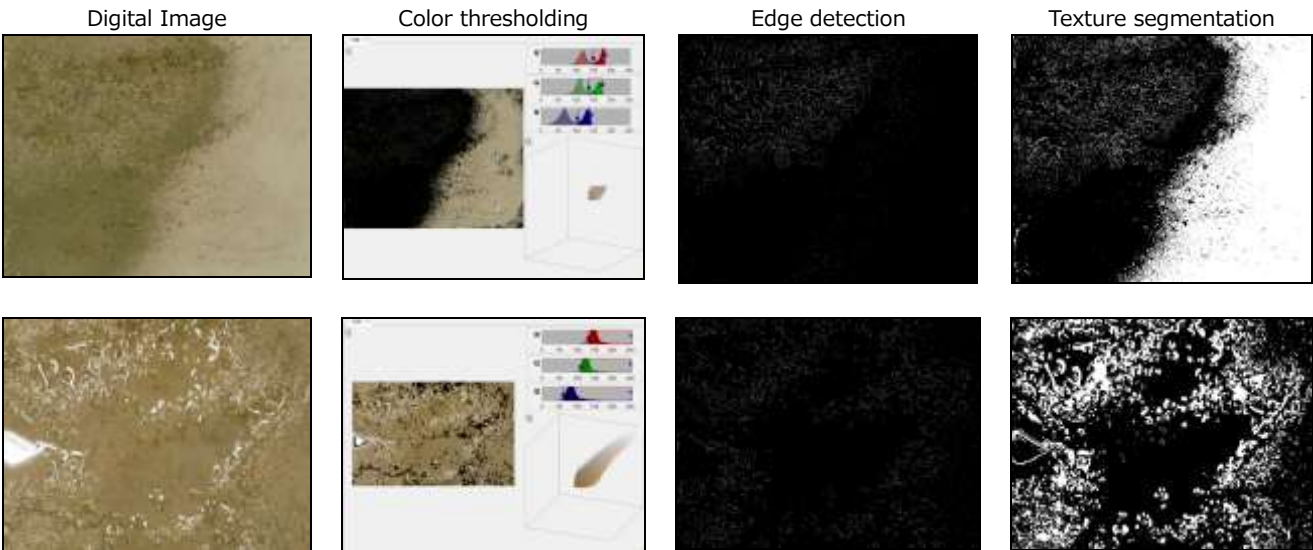


Figure 4: Soil images with dry, surface wet and saturated conditions after image processing

【References】

Pengcheng H., Daming D., Xiande Z., Leizi J., Yun L., 2016. A smartphone-based soil color sensor: For soil type classification, Computers and Electronics in Agriculture 123, 232- 241