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Mapping Malaysian Urban Environment from Airborne Hyperspectral Sensor System in the VIS-NIR (0.4-1.1 μm) Spectrum

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ABSTRACT

Airborne hyperspectral remote sensing is a relatively new technology in Malaysia that needs to be tested for its feasibility. Various applications can benefit from the enormous potential offered such as in urban mapping in which rapid development in Malaysia can be accurately monitored. However, the use of hyperspectral data will also depend critically on the selection of suitable classifiers in order to extract the information. Hence, in this study, image classification was performed using various classifiers such as Parallelepiped, Minimum Distance, Mahalanobis Distance, Maximum Likelihood (ML), Spectral Information Divergence (SID), Spectral Angle Mapper (SAM), Binary Encoding (BE), Neural Network (NN) and Support Vector Machine (SVM). The accuracy of the classifiers was measured based on comparisons with ground truth data. SVM classifier shows the highest overall accuracy (87.98%) followed by ML with 83.17% and BE achieved the lowest accuracy with 39.28%. The findings indicate the feasibility of hyperspectral remote sensing for mapping urban environment in Malaysia with SVM as the most effective classifier for that purpose.

Key words: High resolution, spectral, land cover, built-up, image processing

INTRODUCTION

Urban environment needs certain methodology, technique and model in order to monitor and evaluate all the complex processes in it (Dhaimat and Shawabkeh, 2006). Remote sensing is one of the important tools developed during the past three decades for studying the complex earth's landscape. Varying environment from far distance, under a wide view range and on a temporal basis can be monitored using this tool. Hyperspectral Remote Sensing (HRS) is the latest remote sensing technology for various applications such as environment, agriculture, marine, urban and others (Dowman, 2011). The urban environment is very complex and challenging for the mapping process using remote sensing technology, that it is not optimistic to assume that a single sensor can provide all the information that may be required for its characterization (Gamba *et al.*, 2005). Urban mapping is important for determining the land use and development pattern as well as to study urban heat island analysis and engineering structures integrity.

Dell'acqua *et al.* (2005) in their work argued that very high resolution in the spectral sense is more valuable than in the spatial sense with respect to urban land cover mapping. It might be more useful to have more bands recorded by a sensor than a more detailed image of the scene. The reason for this behaviour is the similarity of many covers due to their very similar chemical components. This motivates the increasing use of hyperspectral data for urban-related applications. However, despite that, the use of hyperspectral data for land cover classifications will be more complicated and inaccurate if the optimal classifier in image processing is not identified or used (Pal and Mather, 2006). Thus with regard to the research problem identified, the objective of this study is to determine the best classifier in urban area using hyperspectral image in visible and near-infrared (VIS-NIR) spectrum. Classification accuracies will be calculated for each of the classifiers used in this study. Furthermore, this study will provide an insight into potential use of hyperspectral data for urban studies in Malaysia. In the Malaysian context, the use of hyperspectral data for mapping urban environment has never been performed extensively and this particular research will serve as a pioneering effort.

MATERIALS AND METHODS

The study area for this research is located at the southern part of Universiti Putra Malaysia (UPM) campus, located in Selangor, Malaysia. It consists of a mixture of academic buildings and natural features which can be categorized as a typical built-up or urbanized area. The airborne hyperspectral data set were acquired from an Advanced Imaging Spectrometer for Applications (AISA) sensor with a spectral range from 400-970 nm (VIS-NIR) consisting of 20 spectral bands. The spatial resolution of the geocorrected image is 1 meter and was captured in 2004 by Aeroscan Precision (M) Sdn Bhd, a private airborne mapping company. The characteristics of the spectral bands are given in Table 1.

Pre-processing was carried out with ENVI 4.5 software for radiometric correction, spectral ratioing and Minimum Noise Fraction (MNF) transformation for noise reduction and end-members selection. Then, classification experiments using several classifiers were performed using training and testing pixels. Finally, accuracy assessment was carried out based on the ground truth map in order to evaluate the performance of the different classification algorithms. Figure 1 outlines the flowchart of the methodology adopted in this study.

In radiometric correction, it will remove the atmospheric disturbance factors that occur while the data were captured on-the-fly. The energy recorded on the raw data was in radiance and it is needed to remove this error by transforming it to reflectance. For this correction, various atmospheric models such as Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH), atmospheric removal program (ATREM) and atmospheric and topographic correction (ATCOR) could be used provided that supporting information such as flying height, date of imagery taken (related to atmospheric pressure etc.) and surface height (DEM) are available. In this study,

Table 1: AISA spectral bands and the centre-wavelength of each band

Band	λ (nm)	Band	λ (nm)	Band	λ (nm)	Band	λ (nm)
1	443.7250	6	586.6250	11	711.0900	16	773.5350
2	462.6250	7	625.8400	12	706.2600	17	810.6220
3	489.4000	8	671.8750	13	726.9600	18	844.2600
4	520.9000	9	694.0400	14	740.7600	19	856.3350
5	557.6400	10	704.2700	15	754.5600	20	889.1100

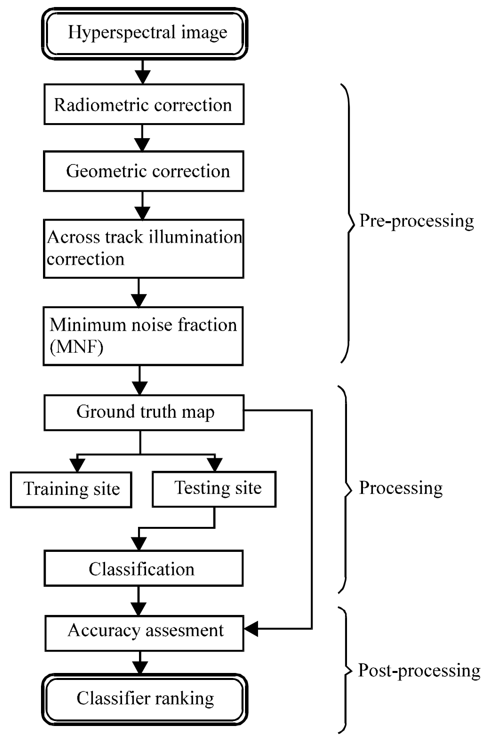

Fig. 1: Methodology of the study

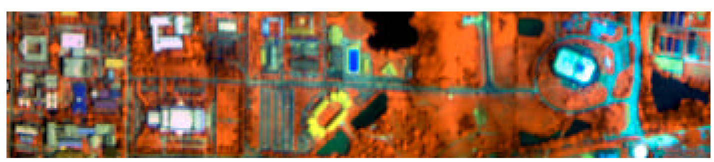

Fig. 2: The study area acquired using AISA sensor (RGB: 14,8,2)

that information is not available, thus simpler method known as the Empirical Line method was employed. A false colour image of the study area is shown in Fig. 2 using Red Green Blue (RGB) bands combination of bands 14, 8 and 2.

Then, the MNF transformation was performed to reduce noise in the data as well as to determine the inherent dimensionality of the data to reduce computational load. After these steps were completed, the image end-members were extracted to be used in the subsequent classification experiments.

In order to generate a ground truth image, a field study campaign was carried out. The photos of the ground targets are shown in Fig. 3 together with their GPS coordinates in WGS84 coordinate systems. Figure 4 shows the ground truth image generated based on the pixels of identified land cover classes during field observation. Table 2 describes the total number of pixels set as training and testing pixels for image classification and accuracy assessment.

Based on the ground truth image, random sampling was carried out to select the pixels for training and testing the classifiers. Different pixels were selected for training and testing to avoid bias in the accuracy assessment process. Figure 5 shows the testing and training pixels.

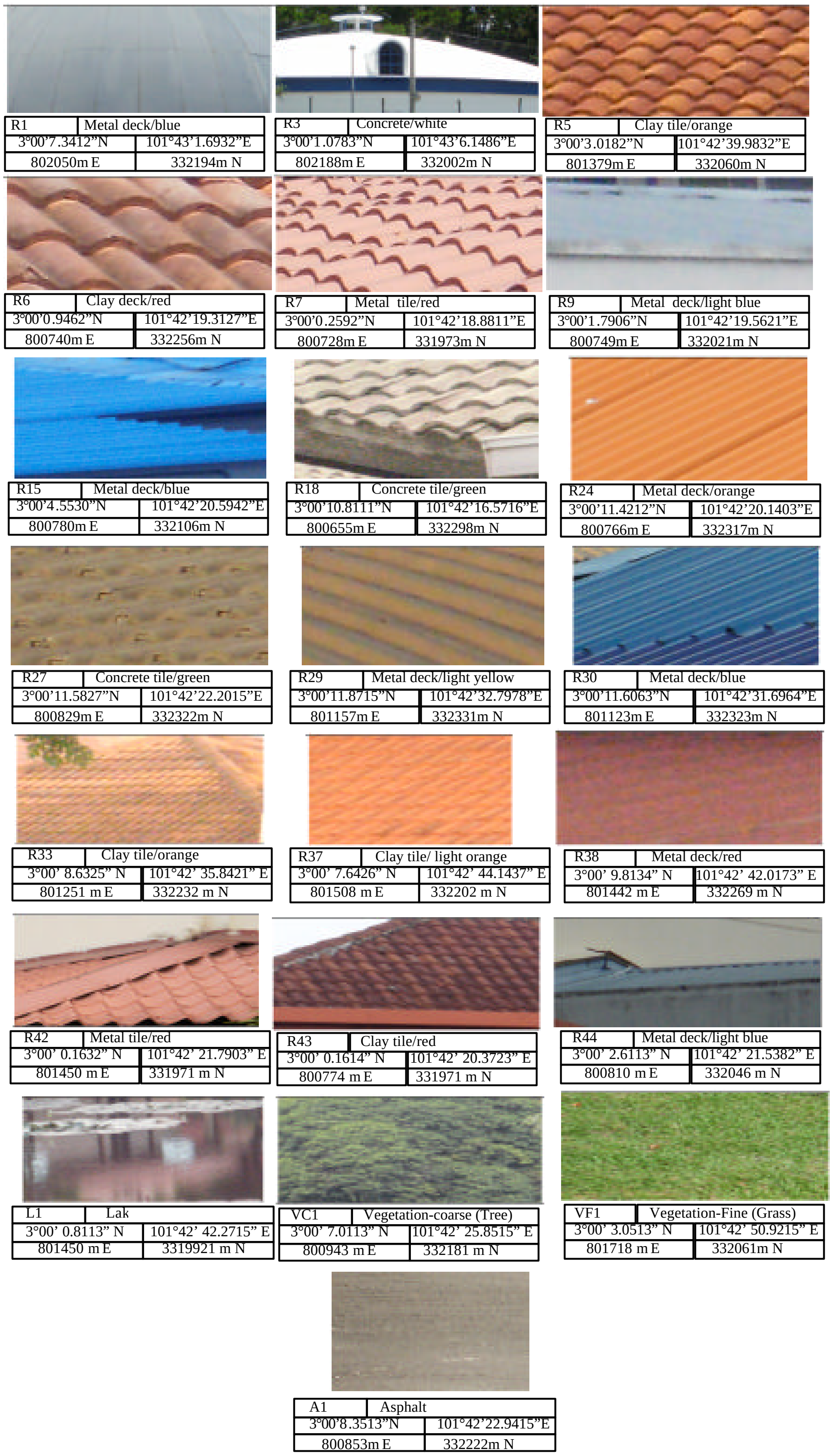

Fig. 3: Photos of ground truth targets

Table 2: Information on the classes, training and testing pixels

Class N	Information class	No. of training pixel	No. of testing pixel
1	Asphalt	9493	19029
2	Clay Tile Light Orange	94	126
3	Clay Tile Orange	283	3253
4	Clay Tile Red	217	560
5	Concrete Tile Green	260	1245
6	Concrete White	204	569
7	Lake	902	24729
8	Metal Deck Blue	399	728
9	Metal Deck Light Blue	203	686
10	Metal Deck Light Yellow	169	276
11	Metal Deck Orange	215	325
12	Metal Deck Red	214	841
13	Metal Tile Red	211	546
14	Swimming Pool	205	626
15	Vegetation Coarse	167	1525
16	Vegetation Fine	1016	2638
Total		14252	57702

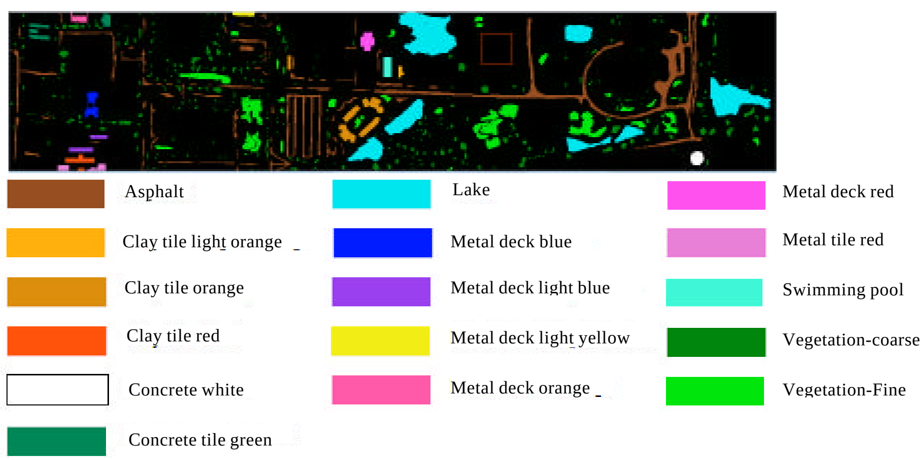

Fig. 4: Ground truth image

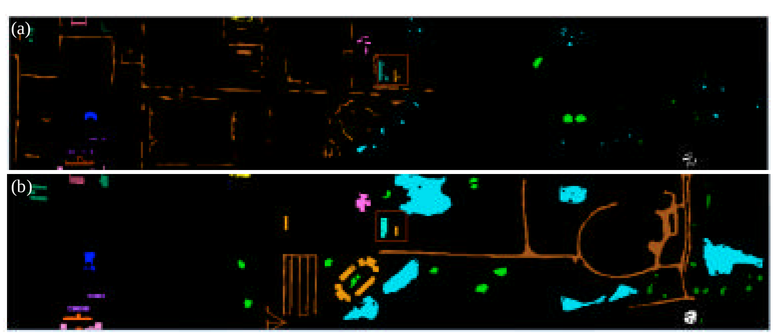

Fig. 5(a-b): (a) Pixels for training and (b) testing sites

CLASSIFIERS

Brief descriptions of classifiers used in this study are described in existing literatures; Parallelepiped, Maximum Likelihood (ML), Minimum Distance, Mahalanobis Distance (Richards and Jia, 1999), Spectral Angle Mapper (SAM) (Kruse *et al*., 1993), Binary Encoding (BE) (Mazer *et al*., 1988), Support Vector Machine (SVM) Benediktsson *et al*. (2007) and Sherrod (2010), Spectral Information Divergence (SID) (Du *et al*., 2004) and Neural Network (NN) (Bryant, 1989; Kang and Park, 2009).

Then classifications on the testing site were carried out using the classification algorithms and finally accuracy assessment was performed. The accuracy of the classifiers was determined by comparing the image processing output with ground truth map generated from ground data collection.

RESULTS AND DISCUSSION

A summary of the classification accuracy results is presented in Table 3. The results are ranked based on the performance of the classifiers.

Overall, the SVM classifier shows the highest overall accuracy (87.98%). This is followed by ML with 83.17% and BE achieved the lowest accuracy with 39.28%. The SVM that was designed for limited training set is proved to be excellent for urban datasets in this study. This could be the reason why SVM was preferred in classifying hyperspectral urban data Fauvel *et al*. (2008) and multispectral data (Yuhendra *et al*., 2011). The other classification results show low to moderate levels accuracy with SAM performed badly for the data. NN might not be optimally designed and yields only about 60% accuracy. The use of NN is also more complicated as the computing time needed for NN training and classification is very demanding (Mahi and Izabatene, 2011).

Figure 6 shows the classified image of the study area using the SVM classifier with the best accuracy level compared to other classifiers. The classified data from remote sensing can later be integrated into a GIS for infrastructure management and monitoring in a more holistic approach (Jain and Subbaiah, 2007). The findings of this study are also consistent in terms of the feasibility of HRS data for urban area in the VIS-NIR region as shown by Ben-Dor (2006). The effectiveness and robustness of SVM have been reported by many researchers such as

Table 3: Classifiers' accuracy

Classifiers	Accuracy (%)
Support vector machine	87.98
Maximum likelihood	83.17
SID (0.05)	82.31
Mahalanobis distance	82.06
Parallellepiped	74.81
SID (0.10)	74.32
Minimum distance	72.62
SAM (0.1 rad)	72.58
SID (0.15)	70.30
SAM (0.2 rad)	66.29
SAM (0.3 rad)	63.85
Neural network	60.18
Binary encoding	39.28

Fig. 6: Classified image of study area using SVM

Pal and Mather (2003, 2004), Mercier and Lennon (2003), Melgani and Bruzzone (2004), Shafri *et al.* (2007), Shafri and Ramle (2009) and Tarabalka *et al.* (2010). Based on this, it is further confirmed that SVM is superior for urban mapping using hyperspectral sensing system.

CONCLUSION

In this study, the feasibility of HRS for urban area is assessed for a tropical Malaysian environment using hyperspectal sensor onboard an aircraft. It was observed that the use of HRS data in the VIS-NIR spectrum (0.4-1.1 μm) is effective for extraction and mapping of urban features in Malaysia. Despite the limited spectral information in comparison with the use of full range (0.4-2.5 μm), it is still sufficient for accurate mapping. This gives an implication on the cost consideration for an airborne mission as VIS-NIR airborne campaign is significantly cheaper in comparison with the use of full range airborne mission in the VIS-NIS-SWIR (visible-near infrared-shortwave infrared) electromagnetic spectrum.

In addition, comparison of the performance of different image processing classifiers reveal the superiority of SVM as the most effective and robust classifier for information extraction from the HRS imagery. The promising results from this research indicate the great potential in the use of HRS for urban mapping in Malaysia and SVM facilitates user friendly and simple approach in mapping with high accuracy.

Further study might include spatial components such as morphological profiles, texture, size and shape into the classification strategy.

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