International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:8, No:10, 2014

A Novel Spectral Index for Automatic Shadow Detection in Urban Mapping Based On WorldView-2 Satellite Imagery

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Abstract**—**In remote sensing, shadow causes problems in many applications such as change detection and classification. It is caused by objects which are elevated, thus can directly affect the accuracy of information. For these reasons, it is very important to detect shadows particularly in urban high spatial resolution imagery which created a significant problem. This paper focuses on automatic shadow detection based on a new spectral index for multispectral imagery known as Shadow Detection Index (SDI). The new spectral index was tested on different areas of WorldView-2 images and the results demonstrated that the new spectral index has a massive potential to extract shadows with accuracy of 94% effectively and automatically. Furthermore, the new shadow detection index improved road extraction from 82% to 93%.

Keywords**—**Spectral index, shadow detection, remote sensing images, WorldView-2.

I. Introduction

In urban remote sensing, shadows are mutual features in images. In recent years with advent of optical sensors with very high resolution more details of the surface conditions can be detected. However there are even more shadows when the resolution is higher and the effects can be remarkable; therefore, analysis of these types of data requires more complex processing techniques to detect and deal with these new tasks.

With the advent of new sensors with high spatial resolution concern of shadows affected by the geometry of the sight has become notably growing for landscape such as urban environment [1]. In urban remote sensing this is a main source of misclassification in extracting land cover information [2].

Normally shadows are divided into two classes: self and cast [3]. A self-shadow is defined by direct light which is not illuminated as a part of the object; a cast shadow is defined by the direction of the light source in the object. These two types of shadows have a different brightness value and usually self-shadow have more brightness value against cast shadow since close illuminated object receive more secondary lighting [1].

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In general shadows can be distributed into three categories in remotely sensed imagery: 1) Cloud shadows. 2) Shadow by natural features. 3) Shadow by urban features.

Usually the shadow problem can be solved into two parts: shadow detection and shadow removal. A lot of studies have considered the problems in the first step which is detecting [1], [4]-[8], and some studies focused on removing shadows from high spatial satellite imagery such as Quickbird and IKONOS, as in [4], [5], [9]. There have been several researches on the detection of shadow in remotely sensed imagery, detection shadow and cloud automatically, as in [10], shadow extraction based on object oriented [11], the Self-Adaptive Feature method [12]; nonetheless, these methods are more useful for very particular application and there are some literatures on shadow detection methods; however, most of them only deal with video sequences [13] and photographic images, as in [14].

With adherence to the above-mentioned points, there is a lack of spectral index which can detect shadows automatically in high spatial resolution imagery especially using WorldView-2 (WV2) satellite. Thus in this paper, the research has been conducted to detect shadows in high spatial resolution imagery with the new spectral index which is applied on WV2 image and the results shows that the shadows can be accurately extracted. This index can be used to solve one of the biggest issues in multispectral imagery which can lead to classification improvement. In addition, this index can be used in different applications. Finally, in this paper effect of shadow index is considered on road extraction as a part of application and results show that the new spectral index can be used in improvement of road extraction using WV2.

II. Method

A. Study Area

The study area of this research is the campus of Universiti Putra Malaysia (UPM), Serdang, Selangor which is covered by different types of pervious and impervious surfaces. This area is located between 3°00′34.05″N, 101°43′19.77″E (Fig. 1).

It is surrounded by residential and natural surroundings totaling to 10 km^2. The study area is covered by a large number of tall trees and different types of buildings which are enclosed by roads in some places and cause low or zero spectral values in the shaded areas of the roads.

In order to apply the new spectral index, different study area over the UPM campus area has been chosen as is shown in (Fig. 2).

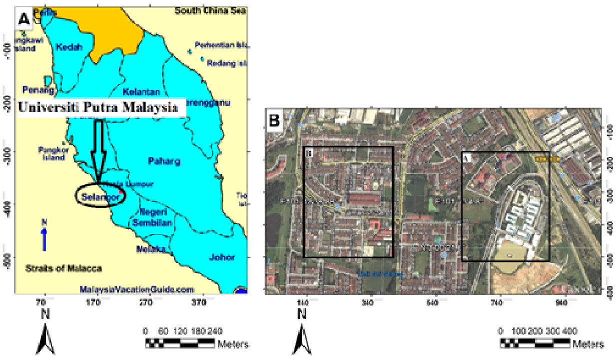

Fig. 1 (A) Map of Malaysia, (B) Study areas from Universiti Putra Malaysia (UPM) campus

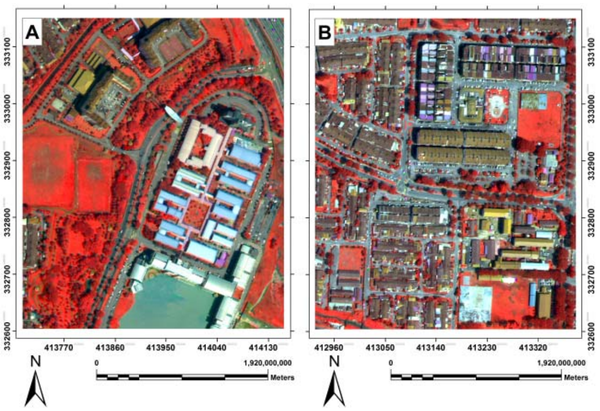

Fig. 2 (A) WV2 imagery over UPM in the main study area, (B) different study area

B. Data Sets and Pre-Processing

The WV2 data used in this research was captured in January 2010 (Fig. 2). It is the first commercially available remote sensing imagery with eight spectral bands. It has 11 bit radiometric resolution and highest viewing angles, ±45 of any VHR imagery, which yields a 1651 km-wide swath [15]. The potential of high spectral and high spatial resolution of WV2 offers flexibility in the classification and discrimination of various urban surface materials and to provide better visualization, the image pan-sharpening was used.

A different subset of WV2 imagery is used in order to evaluate the ability of the new spectral index. The WV2 imagery was geometrically corrected in the UTM projection using zone 47N.

C. Processing and Index Development

A new spectral index is developed to detect the shadows on WV2 imagery. In order to develop the index different bands using band math on ENVI software is utilized. The three bands (Blue, NIR 1 and NIR2) on WV2 imagery were found to be useful and effective for the detection of shadows on the images automatically. Furthermore in order to assess the accuracy of shadow detection index the confusion matrix approach is used. In addition, this index was applied in different study areas in order to validate and check the transferability of this index. Also, the results of new spectral index were overlaid to the road extracted on WV2 images over the main study area (Fig. 2 (A)). In order to extract the roads SVM rules was used to demonstrate the capability of the new spectral index on improvement of road extraction.

D. Assessment and Validation of Accuracy

To assess the accuracy of the results, we validated the new index in different parts of the main study area (Fig. 2) to evaluate its potential use in WV2 imagery. We utilize a confusion matrix to compute the precision of the SDI.

III. Results and Discussion

A. Shadow Detection Index (SDI)

Three bands from WV2 are used to establish a new spectral shadow detection index (SDI) that is fully automated. Table I shows the wavelength ranges of these different bands.

TABLE I
WV2 Bands Used in Shadow Index

Bands	Spectrum Region	Wavelength (Nm)
2	Blue	450—510
7	NIR1	770—895
8	NIR2	860—1040

Equation (1) as a new spectral index is shown. After applying different bands of WV2, three bands were useful to develop a new index that could be helpful to extract the shadow.

$$SDI = \frac{\text{Band 8} - \text{Band 2}}{\text{Band 8} + \text{Band2}} - Band7 \qquad (1)$$

In Fig. 3, the results of applying the index on the images are shown. All objects except shadows are masked and removed after applying the SDI. The results on different study areas showed that the new spectral index is working properly, nonetheless; some very small shadows could not be extracted properly.

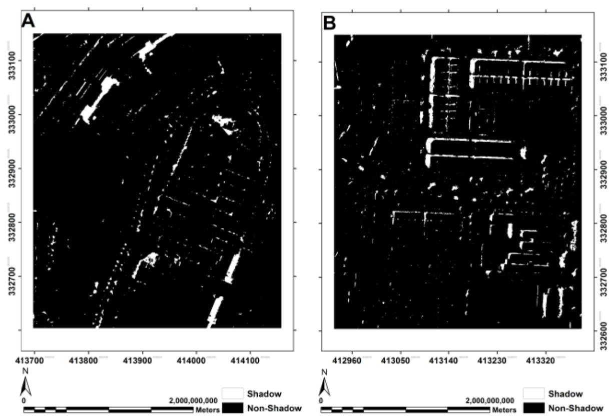

Fig. 3 (A) The results of Shadow Detection Index (B) The results of shadow detection in the different study area

Ground truth data are obtained for accuracy assessment through in situ observation. The table below shows the accuracy assessment of the shadow detection index.

TABLE II
ACCURACY ASSESSMENT USING CONFUSION MATRIX

		Shadow	Non-Shadow	Total	User's Accuracy
Main Study Area	Shadow	48	0	48	100%
	Non-Shadow	26	376	402	93.53%
	Total	74	376	450	
	Producer's Accuracy	64.86%	100%		
	Overall Accuracy	94.22%		Kappa	0.7552

TABLE III
ACCURACY ASSESSMENT OF SDI ON ROAD EXTRACTION

		Road	Non-Road	Total	User's Accuracy
Road Extraction Using SVM	Road	574	87	661	86.86%
	Non-Road	266	1071	1337	80.10%
	Total	840	1158	1998	
	Producer's Accuracy	68.33%	92.49%		
	Overall Accuracy	82.33%		Kappa	0.6265
		Road	Non-Road	Total	User's Accuracy
Road Extraction Using SVM + SDI	Road	805	97	902	89.25%
	Non-Road	35	1061	1096	96.81%
	Total	840	1158	1998	
	Producer's Accuracy	95.83%	91.62%		
	Overall Accuracy	93.39%		Kappa	0.8658

The accuracy assessment results of both study areas show that shadows were extracted for the main area with validation accuracy of 94%.

B. Improvement of Road Extraction Using SDI

In order to evaluate the accuracy and effectiveness of SDI the roads on main study area (Fig. 2 (A)) was extracted using SVM rules with accuracy of 83%. In this part, the result of road extraction is compared with the results of road extraction using SVM rules after applying the SDI on the WV2 image. The efficiencies of these two results were compared with regard to the extraction of impervious pixels such as road after removing the effect of shadow, as presented in Fig. 4.

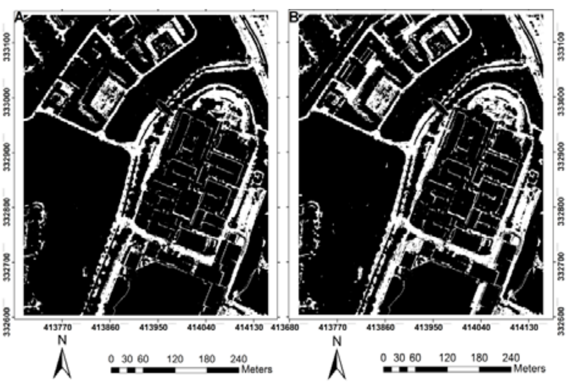

Fig. 4 (A) Results of road extraction using SVM rules (B) overlay the SDI on the road extracted result

Based on the confusion matrix, the accuracies of both results are assessed in the same study area. Thus, ground-truth data is used in the quantitative assessment on road extraction before and after applying the SDI. The evaluation results are shown in Table III.

In this research, we generate new SDI and applied it in two different steps as follows.

In the first step, three bands are selected in order to develop the new spectral index. The wavelengths from visible and near-infrared regions are used to develop the shadow detection index. We obtained ground-truth data for accuracy assessment through in situ observation. To evaluate the proposed SDI, two different areas are conducted on WV2 image and the SDI is used to extract shadows. The shadow positions were accurately and reliably extracted (Fig. 3) and the shadow map is created using the three selected bands (blue, NIR1 and NIR2). However, the SDI did not extract small portion of shadows properly. Hence, the obtained accuracy of shadow extraction is acceptable.

In the second step, SVM rule is used to extract the roads. To assess the SDI, we applied it on the results of road extraction. With the SDI, the roads extracted from main study area were accurate and increased from 82% to 93% after overlaying. The accuracy of road extraction from the main study area was higher and significant. Thus, this index can be used in automatic shadow detection, in addition it can be helpful in different application such road extraction to improve the results.

IV. CONCLUSION

This paper presents a new methodology based on a spectral index for shadow detection automatically. The experimental results show that the proposed method can distinguish dark object from shadows and can extract shadows correctly. The method is simple yet effective and gives more advantages over the use of spectral-based classification for shadow detection and can be extracted quite accurately from other existing methods. Furthermore, three bands can differentiate between shadow and non-shadow areas. In this procedure, the blue, NIR1 and NIR2 bands are ideal for SDI. Moreover, the method is fast without any requirement for collecting training data. A limitation with the current approach is that it cannot extract the small portion of shadow. Despite this limitation, the results of shadow detection are generally accurate. The proposed method is confirmed to be effective by extensive tests using all of the data from WV2 imageries. In addition, it reached minimum accuracy of 94% in shadow detection. The accuracy of the index and the results of the shadow detection were satisfactory.

The experimental results shows that it can be helpful for some applications such as road extraction and pavement condition mapping where shadows are obviously can be seen.

Furthermore, the SVM pixel-based classification rule is used to extract roads. The proposed method on shadow detection is confirmed to be effective on improvement of road network extraction and it could enhance the accuracy of extraction from 82% to 93%.

Future research can test this index to remove the effect of shadow on multispectral imagery especially in urban tropical region since it is covered by clouds and different types of trees to classify and detect some other impervious surfaces.

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