AUTOMATIC SHADOW DETECTION IN HYPERSPECTRAL VIS-NIR IMAGES

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ABSTRACT:
Depending on the landscape type high amounts of shadow can be present in remote sensing images. These areas are usually masked using shadow detection techniques and excluded from further analysis. Although significant research has been conducted on the detection of shadows there is still room for improvements. In this investigation we focus on the development of a new shadow detection algorithm capable to be automatically applied without user knowledge on any hyperspectral VIS-NIR image and thus can be implemented in automated pre-processing chains. The analysis is strictly focussed on the VIS-NIR part of the electromagnetic spectrum due to the growing number of VIS-NIR imaging spectrometers. The developed approach consists of two main steps, the selection of potential shadow pixels and the removal of no-shadow pixels from this mask. In this context the separation between shadow and water is the most challenging task. By analysing different images containing inland and ocean water types we found the slope of the reflectance spectrum of water at specific spectral wavelengths within the VIS-NIR range to be a diagnostic feature for water identification. However, the presence of these features depends on the spectral superimposition of water constituents and bottom coverage. These aspects have been considered in the development of a knowledge-based classifier. First results indicate the great potential of the developed algorithm for urban, rural and coastal scenes of different sensor data (AISA, HyMap).

1. INTRODUCTION

Depending on the landscape type high amounts of shadow can be present in remote sensing images. Detection and delineation of shadow areas can be helpful because shadows carry context information useful for image classifications and allow the derivation of object height information. Another reason for the application of shadow detection algorithms could be the need of restoring the underlying true surface reflectance for further analysis. In this case shadow detection represents a necessary step after which de-shadowing algorithms (Adler-Golden et al., 2002, Richter & Müller, 2005) can be applied.

Although significant research has been conducted on the detection and delineation of shadows there is still room for improvements. For instance, many algorithms need post-processing using morphological filters to fill gaps and eliminate small falsely detected regions (Arevalo et al., 2008, Xia et al., 2009). Others need scene-dependant thresholds or training information to be selected manually (Yamazaki et al., 2009), work only on multitemporal images (Wang et al., 1999), depend on digital surface models (DSMs) as supplementary data (Sohn & Yun, 2008) or show high false-alarm rates in case of water presence (Adler-Golden et al., 2002). To sum up, issues for further improvements include the process automation, the removal of the need of multitemporal or supplementary remote sensing data as well as the detection accuracy.

In this investigation we focus on the development of a new shadow detection algorithm that can be automatically applied without user knowledge and supplementary data on any monotemporal hyperspectral VIS-NIR image and thus, can be easily implemented in automated pre-processing chains. The analysis is strictly focussed on the VIS-NIR part of the electromagnetic spectrum due to the growing number of VIS-NIR imaging spectrometers. The developed approach consists of two main steps, the selection of potential shadow pixels (section 3.1) and the removal of no-shadow pixels from this mask (sections 3.2 and 3.3). In this context the separation between shadow and water is the most challenging task which is implemented by consecutive spectral and spatial processing steps (sections 3.3.1 and 3.3.2) resulting in very high detection accuracies.

2. TEST SITES AND DATA

Urban, rural and coastal landscapes have been selected to test the applicability of the approach for different environments. Five test sites, each 350 x 500 pixels, from 4 flight lines (Table 1) have been selected for validation. All of them are situated in Germany in
the city of Berlin, the city of Potsdam, a heathland region near Potsdam called “Döberitzer Heide”, and the North Sea island Heligoland.

The analysed datasets comprise data from the sensors AISA Eagle and HyMap. The AISA Eagle sensor is an airborne VIS-NIR pushbroom scanner (400 – 970 nm) with 12 bit radiometric resolution and variable spectral binning options resulting in spectral sampling intervals between 1.25 nm and 9.2 nm (Ltd., 2011) and 488 to 60 spectral bands, respectively. The HyMap sensor is an airborne VIS-NIR-SWIR whiskbroom scanner consisting of four detector modules with average spectral sampling intervals of 15 nm (VIS and NIRS), 13 nm (SWIR1) and 17 nm (SWIR2) (Cocks et al., 1998). The 128 spectral bands cover the spectral region from 440 nm to 2500 nm. The radiometric resolution is 16 bit.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Test site</th>
<th>Acquisition date and time (UTC)</th>
<th>Flight height</th>
<th>Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>AISA Eagle</td>
<td>Heligoland</td>
<td>09.05.2008 08:33</td>
<td>693 m</td>
<td>1 m</td>
</tr>
<tr>
<td>AISA Eagle</td>
<td>Döberitzer Heide</td>
<td>19.08.2009 11:00</td>
<td>1280 m</td>
<td>2 m</td>
</tr>
<tr>
<td>HyMap Eagle</td>
<td>Potsdam</td>
<td>07.07.2004 10:30</td>
<td>1950 m</td>
<td>3.5 m</td>
</tr>
<tr>
<td>HyMap</td>
<td>Berlin (two subsets)</td>
<td>20.06.2005 10:13</td>
<td>1960 m</td>
<td>3.5 m</td>
</tr>
</tbody>
</table>

Table 1: Flightline-specific characteristics

The spectral resolutions of the AISA datasets are 2.3 nm for Döberitzer Heide and 4.6 nm for Heligoland.

3. METHODS

Shadow detection is a trivial task as long as there are no dark surfaces present in the image. Unfortunately, the only common spectral characteristic of all shadow pixels - shadowed pixels are very dark – also applies to a couple of non-shadowed surfaces such as water, dark rocks (e.g., lava, basalt) or bituminous roofing materials. To account for this, we developed a two-step approach that firstly masks low reflectance targets as potential shadow pixels (section 3.1) and secondly applies a process of elimination to consecutively remove false positives (sections 3.2 and 3.3).

3.1 Masking potential shadow pixels

The atmospheric conditions during data acquisition have an influence on the reflectance level of shadow pixels after atmospheric correction due to the different amount of light that is scattered into the shadow areas. This effect is usually not accounted for during atmospheric correction since it requires a mask of shadow pixels. Therefore, in order to automatically mask potential shadow pixels according to their low reflectance level, an individual image-specific threshold must be determined per image. Such a threshold could be determined by simulating a shadow image from the original image by virtually casting a shadow over the complete scene to search for the brightest possible shadow pixel. This is done by multiplying each pixel spectrum of the original image with the proportion of diffuse irradiation which is calculated by MODTRAN based on the dataset-specific parameters sun position, viewing geometry, geographic location, terrain elevation and the estimated atmospheric parameters atmospheric optical thickness (AOT) and column water vapour (CWV).

The shadow image shows how bright shadow pixels can be under the respective conditions during data acquisition. From a graph of sorted spectral mean values of all pixel spectra (Figure 1) the desired threshold for the brightest possible shadow pixel can be selected. The maximum of this graph represents not a proper threshold because pixels situated on the right-hand raising tail of the graph are pixels of specular reflection. Since specular reflection can not occur within shadow areas the reflectance level of these simulated shadow pixels can not occur in reality and would consequently lead to the inclusion of non-shadow pixels in the mask of potential shadow pixels. In order to exclude pixels of specular reflection and automatically select the highest point on the left of the right-hand raising tail the point of maximum curvature $\text{MAX}(\kappa)$ (Equation 1) at a reflectance level greater than 2.5 % is calculated. The 2.5 % condition avoids the threshold for being placed at the left end of the graph where the original shadow pixels are situated. The functions $f'$ and $f''$ in Equation 1 are calculated by approximating and differentiation $f$ using a Savitzky-Golay filter (Savitzky & Golay, 1964).

$$\kappa = \frac{f''(x)}{\left(1 + f'(x)^2\right)^{\frac{3}{2}}} \quad (1)$$

where $\kappa$ = curvature

$f', f''$ = 1st and 2nd derivation of the approximated function $f$
The application of the automatically calculated image-specific thresholds as maximum thresholds on the spectral mean values of the original image results in masks of potential shadow pixels (Figure 2). Some of the dark surfaces, e.g. asphalt and bituminous roofing materials, are already mostly excluded by the application of this threshold. The majority of dark but not shadowed surfaces that are still included in the mask are water pixels with or without aquatic plants. The removal of these pixels is described in sections 3.2 and 3.3.

**Figure 2. Mask of potential shadow pixels (right-hand) for the test site Potsdam.**

### 3.2 Removal of aquatic plants

Spectra of aquatic plants are characterized by spectral features of vegetation, such as the red edge and the chlorophyll absorption features at 610 nm and 675 nm. A removal of pixels with these spectral characteristics would also remove pixels of shadowed vegetation on land which also show these features while the spectra of both surfaces have a comparable low albedo (Figure 3). A diagnostic spectral difference between both surfaces can be found in the NIR region where the water absorption causes the spectra of aquatic plants to decrease between 710 – 740 nm as well as 815 – 880 nm. Therefore, pixels of aquatic plants can be removed from the mask of potential shadow pixels using the condition:

\[
VI^* > 1.0 \quad \text{AND} \quad (R_{740} - R_{710}) / 740 - 710 < -0.001 \quad \text{OR} \quad R_{880} - R_{815} / 880 - 815 < -0.01
\]  

where  
\[
VI^* = \frac{\max(R_{710}, R_{720})}{R_{680}}
\]  
\[
R_{740} = \text{reflectance at wavelength 740 nm}
\]  
\[
\text{Reflectance values must be scaled between 0 – 100}
\]
Figure 3. Spectra of aquatic plants (or algae) in comparison with a spectrum of shadowed vegetation on land. The blue bars mark the
wavelength of the two ratios used for distinguishing both surface types.

3.3 Removal of water pixels

Water and shadow spectra are on average both very dark. The reflectance level of both decreases with wavelength due to a
decreasing proportion of diffuse irradiation in the case of shadow and due to the increasing light absorption in the case of water.
Additionally, both show a high spectral variability due to different types of shadowed surfaces (case of shadow) and due to varying
water constituents and bottom reflection (case of water). However, despite this variation all water spectra have one thing in common:
the pure water itself. Therefore, spectral features of pure water, especially absorption features, can be seen in every spectrum of
water. However, the presence of these spectral features depends on the spectral superimposition of the water constituents and bottom
coverage. Section 3.3.1 describes how these aspects can be considered in the development of a knowledge-based classifier for
spectrally distinguishing water and shadow. Section 3.3.2 then continues with a spatial post-processing.

3.3.1 Water detection based on spectral slopes: Figure 4 shows the absorption spectrum of pure water (logarithmic scale) in
comparison with selected reflectance spectra of different water bodies of the analysed datasets. It can be seen that the increasing
absorption within specific wavelength intervals (1st, 2nd, 4th and 5th light red bar) results in decreasing reflectance for most of the
reflectance spectra. The 3rd light red bar represents a short wavelength interval of stagnating absorption where some water spectra
temporarily raise due to increasing reflectance of water constituents or water bottom before decreasing again. However, these effects
are not present within all wavelength intervals of all water spectra because they can be superimposed by the reflectance of the water
constituents and water bottom. In order to find the slope combinations that can occur for typical water bodies we analysed 112,041
spectra of several types of water bodies (rivers, lakes, ponds, North Sea), fitted a first-degree polynomial to the parts of the spectra
within the wavelength intervals using the least squares method, and coded each slope as 1 if the algebraic sign of the slope meets the
expectation and 0 if not. This results in a five-digit binary vector for each analysed water spectrum representing the co-occurrence of
slopes within the respective diagnostic wavelength intervals that meet the expectations. The 2^5 possible binary vectors are numbered
from 0 to 31 whereas the 0 vector (none of the 5 slopes met the expectation) was excluded from further analysis. The numbered
combinations are shown in Figure 5 in comparison with the numbered combinations of 33,721 analysed shadow spectra. It can be
seen that many combinations are occupied either by water or by shadow spectra and thus provide a clear separation between water
and shadow. These combinations are implemented in the developed approach so that spectra that are identified as water due to a
certain combination of slopes can be removed from the potential shadow mask and other spectra can be confirmed as shadow.
However, the combinations marked by the orange arrows are still ambiguous. Pixels that fall into these combinations need a
consecutive spatial post-processing described in Section 3.3.2.

Figure 4. Water absorption (thick blue line, logarithmic scale, source: WASI (Gege, 2005)) in comparison to water reflectance
spectra from different water bodies of the analysed datasets. The increasing absorption within specific wavelength intervals (light red
colors) results in decreasing reflectance for most of the reflectance spectra but is partly superimposed by the reflectance of the water
constituents and water bottom.
3.3.2 Spatial post-processing for water-shadow-separation: Pixels of the potential shadow mask that have not been identified as shadow or water based on the unambiguous spectral slope combinations are subjected to a consecutive spatial post-processing. In this processing the idea is to decide according to the dominating spectral decision made within the neighbourhood of the ambiguous potential shadow pixels (Figure 6). The spectral decisions in the neighbourhood are counted using an iteratively growing NxN pixel neighbourhood starting at N = 15. If no decision can be made in the 15x15 neighbourhood the neighbourhood starts growing until a decision can be made. This results in a water score and a no-water score for each pixel to be checked. The decision is then related to the higher score, i.e. if more pixels within the neighbourhood have been spectrally identified as water the pixel is removed from the potential shadow mask and if spectrally confirmed shadow pixels dominate the neighbourhood the pixel remains in the mask. Finally, pixels that have been confirmed as shadow either during the spectral or spatial processing form the final shadow mask.
In order to assess the accuracy of the developed approach shadow and water pixels have been digitized comprehensively for the five validation subsets. Based on the digitised shadow reference areas a no-shadow class has been created which is everything but the shadows and a two pixel buffer around the shadows because of the mixed pixel problem. Using the reference areas of shadow and no-shadow the probability of detection (POD) and probability of false detection (POFD) for shadows have been calculated given in Table 2. Since the water-shadow separation represents the core of the developed approach the ability of the algorithm to distinguish water and shadow is assessed separately by calculating the user accuracies of the two classes (Table 2).

<table>
<thead>
<tr>
<th>Test site</th>
<th>POD</th>
<th>POFD</th>
<th>UA Shadow</th>
<th>UA Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heligoland</td>
<td>94.5</td>
<td>0.01</td>
<td>99.98</td>
<td>98.5</td>
</tr>
<tr>
<td>Berlin sub1</td>
<td>94.4</td>
<td>0.71</td>
<td>90.1</td>
<td>99.3</td>
</tr>
<tr>
<td>Berlin sub2</td>
<td>95.9</td>
<td>1.38</td>
<td>90.1</td>
<td>86.1</td>
</tr>
<tr>
<td>Potsdam</td>
<td>65.1</td>
<td>0.0</td>
<td>92.1</td>
<td>99.99</td>
</tr>
<tr>
<td>Döberitzer Heide</td>
<td>27.9</td>
<td>0.0</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2. Results of the accuracy assessment

Figure 7. Automatically detected shadow and water areas for the five validation subsets Heligoland, Berlin sub1, Berlin sub2, Potsdam, and Döberitzer Heide (top to bottom)
POD and POFD are typical measures for evaluating the accuracy of forecasting methods (Jolliffe & Stephenson, 2003) as well as two-class classification problems like detection tasks (one class of interest and one background class). The POFD of a class, also known as the false alarm rate, measures the fraction of false alarms given the class is not present, i.e. the number of false alarm pixels divided by the total number of ground truth pixels of the background class (= omission error of the no-shadow class). The achieved POFD for the test sites is very low (usually below 1 %) showing that shadow can be well distinguished from non-shadowed surfaces. While it is close to 0 for three of the test sites it is slightly higher for the two test sites of Berlin due to some parts of rivers or lakes that were falsely identified as shadow.

The POD of a class, also known as hit rate, measures the fraction of the detected pixels of the class of interest that were correctly identified, i.e. the number of correctly identified pixels divided by the total number of ground truth pixels of the class (= producer accuracy of the shadow class). The achieved POD for the test sites of Heligoland and Berlin are very high (> 94 %) showing that the developed algorithm is working very well in urban and coastal environments. A decrease of the POD can be observed for the test sites of Potsdam and Döberitzer Heide which is caused by false negatives (missing detection of shadow pixels) in the inner parts of woods and adjacent to single trees (compare Figure 7). It can be assumed that translucent objects such as trees illuminate their shadows by transmitted light. Moreover, surrounding trees reflect and scatter light into the shadows of the other trees. This results in an amplification of the reflectance level of tree shadows. Hence, tree shadows appear brighter than shadows of opaque objects which is contrary to the basic assumption made in the generation of the potential shadow mask in Section 3.1 that the only source of light within shadows is diffuse sky light. Consequently, tree shadows (except those of the edges of woods which are dark enough) are not included in the potential shadow mask. This has to be improved in the future.

The user accuracies of the shadow-water separation – the core of the developed algorithm – are very high compared to classification results of other studies (e.g., Carleer & Wolff, 2006). This shows that shadow and water areas can be well distinguished based on physical absorption features of water using imaging spectroscopy data. The highest confusion occurs for small water bodies of the Berlin test sites which might be caused by adjacency effects.

5. CONCLUSION

A new algorithm for detecting shadows based on VIS-NIR imaging spectroscopy data has been developed. The proposed approach does not require *a priori* knowledge or tuning of input parameters and is able to automatically detect shadows of opaque shadow casting objects with a very high accuracy. The algorithm works for different sensors (tested on AISA Eagle and HyMap), works for different types of landscapes (tested: urban, rural and coastal) and also works for different atmospheric correction methods (tested: ATCOR-4 (Richter, 2011), MIP (Heege & Fischer, 2004), ACUM-R (unpublished in-house development by K. Segl), the method of L. Guanter et al. (Guanter et al., 2009), and empirical line correction). Future development will be focussed on the inclusion of tree shadows into the potential shadow mask. Further tests will also consider cloud shadows and shadow on water.

REFERENCES


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