FEATURE BASED FUSION OF MULTISENSOR DATA - INCLUSION OF HYPERSPECTRAL DATA INTO CLASSIFICATION OF HIGH RESOLUTION ORTHOPHOTOS

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ABSTRACT

Many applications of remote sensing – like for example urban monitoring – require high resolution data. For a correct determination of object geometry, high spatial resolution data is essential. These data contain often low spectral information like three band RGB orthophotos. Similar feature values for thematic classes like water, dark pavements or dark rooftops lead to classification errors. As a result, high spectral resolution is also needed to separate these classes. Due to technical sensor limitations, hyperspectral data comes with a coarse ground resolution of > 3 m and are thus not suitable for geometric modelling of surface objects. A multisensor fusion is needed to reduce the limitations and uncertainties associated with data coming from a single sensor like described above.

In the context of remotely sensed data, fusion is often performed by combining high spatial with high spectral resolution imagery on different levels. In contrast to pixel-based approaches like the IHS-transformation or PC spectral sharpening, the emphasis of this paper is fusion of data at feature level. Hyperspectral data recorded by the HyMap sensor are fused with high spatial resolution imagery (digital orthophotos) for a combined endmember selection and classification.

In this approach, the endmember for the thematic classes will be determined in a semi-automatic process. After a segmentation of the high spatial resolution dataset the resulting segments will be used to detect those pixels in the hyperspectral data, which represent candidates for the definition of thematic endmembers. The endmembers are stored in a spectral library and are used for the classification of hyperspectral data. The segments in the high spatial resolution data will be processed based upon the classification of the hyperspectral dataset and the application of overlay rules.

Keywords: hyperspectral remote sensing, classification, data fusion, feature level

1 INTRODUCTION

Remote Sensing data used for spatial planning tasks require "high" resolution especially in urban areas. On the one hand, as a precondition for the detection of object shapes, high spatial resolution is necessary. On the other hand, high spectral resolution allows a differentiation of urban surfaces by their material composition due to their characteristic spectra.

However, high spatial resolution imaging sensors like the High Resolution Stereo Camera (HRSC-A) provide less than 10 bands to characterize the spectral feature of recorded data [1]. This low spectral resolution is insufficient to characterize the object’s surface material by it’s spectral characteristic (absorption bands, ratios). Hyperspectral sensors like the Digital Airborne Imaging Spectrometer (DAIS) or the Hyperspectral Image Mapper (HyMap) are able to record the reflecting spectra of an object’s surface with 79 (DAIS) respective 128 (HyMap) bands[2][3]. Due to technical limitations (e.g. sensors scan rate of 10 to 25 Hz) hyperspectral sensors are not able to deliver a spatial resolution of better than 2-3 m across flight track even at lower operating altitudes [4].

If an area of interest is recorded by both sensor types (maybe even co-registered), data fusion techniques are needed in order to retrieve the mutual benefit of both data types. In contrast to pixel based fusion algorithms [1],[5],[6] in this paper we discuss data fusion at feature level [7].

2 STUDY AREA AND DATA ACQUISITION

The study area is located in the centre of the City of Osnabrück (Northwest Germany)(Fig. 1), covering 205x762 m² with different urban surface types. For this study, different datasets were obtained for further investigations:
• Digital orthophoto data
• Digital elevation model (DEM) derived from cadastral data
• Digital surface model (DSM) derived from HRSC-A image data
• Hyperspectral image data

The hyperspectral data (Fig. 1 - left) were taken by the HyMap sensor. Scanned aerial images, taken by the Local Earth Observation System (LEO) [8] represent the image data of high spatial resolution (Fig. 1 - right).

**Figure 1.** Left: Hyperspectral image data with study area (yellow box), Right: Corresponding high spatial resolution data defining the study area.

### 2.1 DIGITAL ORTHOPHOTO SYSTEM

The high spatial resolution data produced by LEO were 5.5cm x 5.5cm airphotos, taken on 16 May 2003 at an average flying height of 500 m. The image scale was about 1:10,000. The photos were scanned and resampled to a spatial ground resolution of 0.125 m. An orthoimage was generated using softcopy photogrammetry software with a resulting horizontal accuracy of $s_{x,y} = 0.2$ m. For further processing steps, the orthophoto was resampled by pixel aggregation to a resolution of 0.5 m.

### 2.2 NORMALIZED DIGITAL SURFACE MODEL

Information about the elevation of surfaces in the study area exist in two datasets:

• Digital elevation model (DEM) derived from cadastral data, gridsize 12.5 m, $s_z = 0.5$ m
• Digital surface model (DSM), produced by DLR on HRSC-A-data [9], gridsize 0.5 m, $s_z = 0.2$ m

The HRSC-A DSM was normalized (nDSM) by use of the DEM data [10]. Unfortunately the HRSC-A campaign has been carried out in April 1999, an early stage of vegetation period.

As a result the height of objects like trees or bushes could not be determined correctly (Fig. 2). As a consequence the differentiation of vegetational objects in classes like "tree" and "lawn" has been left out in further processing.
2.3. HYPERSPECTRAL IMAGE DATA

In 2003 the German Space Centre (DLR) in Oberpfaffenhofen coordinated a campaign on hyperspectral HyMap surveys in Europe (HyEurope2003). During this campaign, on July 15th, the hyperspectral image data were obtained by a north-south transect over the City of Osnabrück.

The HyMap Sensor records 128 reflective bands covering the visible and near infrared range (VNIR) and the short wave infrared domain (SWIR) between 0.4µm and 2.5µm. With an operating altitude of 1500 m and a scan frequency of 16 Hz data could be recorded with a ground projected instantaneous field of view (GIFOV) of 3 m across and 4 m along flight track. The recorded lines of data were geocoded to a raster by parametric geocoding, implemented in PARGE [11]. To maximize the geometric accuracy during the orthorectification process, the nDSM with a grid size of 2 m was used. This oversampling (GIFOV = 3 m) reduced the amount of double-mapped image pixels from 1.8% to 0.3% (nDSM gridsize 3 m vs. 2 m).

The geometric accuracy of the image data was checked by cadastral GIS data (buildings) and estimated to be ±1.8 m (Fig. 3).

3. METHODOLOGY

The methodological approach for data fusion is characterized by object-oriented segmentation for a semi-automatic endmember selection and a "SAM-score" based inclusion of the hyperspectral information in the classification of the high resolution orthophotos:
Segment based endmember selection

For the classification of hyperspectral data, reference spectra or endmembers are necessary. The geometric location of the pixel representing an endmember of an urban surface type is determined by a segmentation of the high resolution image data. Pixel that are fully contained in a segment are candidates for the definition of reference spectra and are considered for the creation of a spectral library.

Classification of image objects

With the user-specific knowledge contained in spectral libraries, the hyperspectral data are classified by the full pixel classification approach Spectral Angle Mapper (SAM). The classification results are transformed to an 8-bit SAM-score by a user-independent automated algorithm (see section 3.2). Due to the poor geometrical resolution of hyperspectral sensors, image data of urban areas contain a vast amount of mixed pixels. As a consequence, at n given endmembers, the presented approach leads to n SAM-scores for a Pixel. This information is used in a second step to classify the segments of the high resolution image data. The end product of this approach is a map produced by the classified segments. The workflow of the presented approach is shown in the following figure:

[Diagram showing the process of segment based endmember selection and classification]

**Figure 4.** Segments of high resolution data (top left) are used for endmember selection in hyperspectral data (top right). Minimum distance (nearest neighbour) classification and score image are fused by using a linear membership function. Results are produced by a neural network classifier of eCognition.

3.1 SEGMENT BASED ENDMEMBER SELECTION

Reference spectra for surface materials can be retrieved from field measurements or derived from image data. In case of a derivation of endmembers from image data, several algorithms have been developed:

- Pixel Purity Index (PPI), implemented in ENVI [14]
- NFIND-R [15]
- Iterative Constrained Endmembers Algorithm (ICE) [16]
- Autonomous Morphological Endmember Extraction (AMEE) [17]

Urban surface endmembers are often a result of the mixture of manmade materials which usually leads to flat spectra. In addition, some of these endmembers have similar spectral features and are hardly separable in feature space. As a consequence, automated algorithms like PPI or manual endmember selection lead to a significantly smaller number of defined urban surface endmembers.

Due to this fact, the geometric location of pixels which represent endmembers are detected by segmentation of high spatial resolution data. The segments are generated by a multiresolution segmentation approach implemented in eCognition [18]. Only pixels of the hyperspectral data which are embedded in a
N-8 neighbourhood that is completely included in the identified image segments are considered for the manual definition of endmember spectra and stored in a spectral library (Fig. 5).

Figure 5. Figure Segment based endmember selection. Left: high spatial resolution data and derived segments. Centre: endmember candidates (yellow) and definition (cyan). Right: Retrieved endmember spectra.

Using this approach for the described study site, for each a priori defined class one endmember was defined except for the classes "asphalt" and "roof/tar". For investigation purposes these classes were defined by a common endmember to investigate if a definition for a general material like "bitumen" is suitable for urban surface materials.

3.2. SAM-SCORE

For the further classification process a score for each pixel of the hyperspectral data has to be determined. The score is calculated by the results of the Spectral Angle Mapper (SAM). The SAM calculates the cosine of a spectral angle for each given reference spectra with the following equation:

$$\cos \phi = \frac{\sum_{i=0}^{n} p_i r_i}{\sqrt{\sum_{i=0}^{n} p_i} \sqrt{\sum_{i=0}^{n} r_i}}$$

where \(\phi\) is the spectral angle, calculated as cumulative sum of the angle between the given image spectra \(p\) and reference spectra \(r\). One result of SAM is a "rule image" which contains \(n\) spectral angles (\(\phi_1...\phi_n\), see eq. 1) for each image pixel at \(n\) given endmember. A value of 0 represents a perfect fit to a given endmember. Low values in the rule image indicate a candidate for the investigated class.

To build the SAM-score for further classification, the spectral angle from the rule image is converted into a 8-bit value using the following equations:

$$s_{c,i} = 255 \frac{\phi_c^{\text{max}} - \phi_i}{\phi_c^{\text{max}} - \phi_c^{\text{min}}}$$

where \(s_{c,i}\) is the score for Pixel \(i\) with respect to class \(c\). The spectral angle \(\phi_c^{\text{max}}\) is describing the best fitting pixel, the determination of this value is no problem since only the smallest rule value for a class has to be find. The angle \(\phi_c^{\text{min}}\) is describing the spectral angle which contains the “worst fitting pixel” of a class. The following algorithm finds this worst fitting pixel: First each pixel’s spectral angles (Eq. 1) are sorted by their value. If the smallest spectral angle (the best fitting class \(i\)) is significant better than the second best, this pixel is marked as candidate for a SAM-score of class \(i\). If the second or even third best spectral angle are near the best fitting angle (\(\phi_i - \phi_j < 0.33 \phi_i\) or \(\phi_k - \phi_i < 0.33 \phi_i\)) the Pixel is also marked as a candidate for a SAM-score of class \(j\) or \(k\) as shown in Fig. 6.
Figure 6. Pixel with lowest spectral angle for class 3 (left) receives highest SAM-score for this class but also a score for classes 4 and 8.

Afterwards for each class the marked pixel will be considered for an estimate of the spectral angles $\varphi_c^{\text{max}}$ and $\varphi_c^{\text{min}}$ which define the limits for the following linear transformation to a 8-bit Score (Eq. 2).

3.3. CLASSIFICATION OF IMAGE OBJECTS

The creation of image objects (segments) and the final classification is performed within the software eCognition. eCognition provides a neural network classifier which allows the user to create feature specific membership functions. As shown in Fig. 7, beneath the RGB-values from the orthophoto additional feature values like SAM-score and the segment’s elevation are available.

Figure 7. SAM-scores and nDSM values as additional feature values for a segment.

The three fuzzy sets (segment’s elevation, RGB feature space and SAM-score) are fused together by linear membership functions for the neural network classifier implemented in eCognition.

4. RESULTS

19 different, visibly similar classes have been defined with a differentiation in material classes in order to prove the methodology. For example, red roof tops were divided into "red roof concrete" and "red roof clay". Three different classification scenarios were defined to investigate the performance of the presented approach. A minimum distance classification applied on the RGB feature space of the orthophoto (RGB) (see Fig. 8) was carried out. For each of the classification scenarios the overall accuracy was estimated.

The first classification, based only on the RGB information of the spatial high resolution image data show typical results for visible similar classes(Fig. 8). As a result of the visible similarity, a high classification confusion could be observed. Also a low overall accuracy of 52% was measured.
The additionally use of the segment’s elevation and the implementation of SAM-scores into the classification process show improved results (see Fig 9). The overall accuracy could be increased up to 75% due to the visible similarities of the defined classes.

5. CONCLUSION

The presented approach uses the benefits of a combination of high spatial and high spectral resolution remote sensing data. It could be proved that a segment based endmember selection results in a suitable spectral library. With an automated score generation, additional feature values for the image segments could be generated. The additional inclusion of hyperspectral image data into a classification process of high spatial resolution image data show significant improvements and allow material differentiation of urban surfaces.

The accuracy of the presented approach is highly dependent on the geometric correctness of the acquired image data. The results are based on image data that are not co-registered. Future co-registered sensor combinations like ARES [19] and HRSC will show if the overall accuracy can be increased.

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REFERENCES


