ABSTRACT

The high spectral resolution of hyperspectral images (HSI) requires a heavy processing load. Assigning each pixel to a group in the image, which is called superpixel, and processing the superpixels instead of the pixels is resorted as a means to overcome this challenge in the hyperspectral literature. In this paper, we propose an algorithm to segment a hyperspectral image into superpixels by means of iteratively updating the boundary pixels of superpixels. We first explore the optimal similarity metric for the boundary pixel updates with the constraint of keeping the superpixel boundaries aligned with the object boundaries in the image. We investigate two approaches for similarity detection between pixels during this update, first comparing the hyperspectral pixels individually, and second, comparing the pixels by using also their neighborhood. The spectral similarity metrics used for investigation are selected as spectral angle mapping (SAM) [1], spectral information divergence (SID) [2] and spatial coherence distance [3] due to their common usage. The proposed approach is compared with a pioneer state-of-the-art superpixel algorithm, SLIC [4], and its superiority is verified in terms of the superpixelization performance metrics, namely boundary recall and undersegmentation error [5].

Index Terms— Superpixel, hyperspectral, spectral metrics, boundary updates, SLIC

1. INTRODUCTION

Hyperspectral imaging has been one of the core research areas in remote sensing and geoscience in recent years with enormous number of applications ranging from video surveillance and environment monitoring to land-cover mapping and agriculture analysis [6]. The mentioned applications have also brought new research problems, such as hyperspectral unmixing, hyperspectral target detection, hyperspectral segmentation and hyperspectral image classification [7]. In most of these applications, decreasing the spatial redundancy between the hyperspectral pixels is encountered as a necessary initial stage for the processing of high resolution hyperspectral images.

Superpixelization [8], which can be defined as the perceptual grouping of pixels, is proposed as a means for this purpose. Since a perceptual grouping of pixels contains more information than the individual pixels and align better to the object boundaries than the other grid based structures, superpixel extraction is utilized as a well known preprocessing step in many computer vision applications, including graph based image segmentation, object recognition and others [9].

In hyperspectral image analysis research, superpixels are used for different special tasks. Since hyperspectral images are formed of a large size data due to the high spectral resolution, the processing stage is not easy in terms of computation time. Superpixels are used in order to reduce the size of the image to alleviate the processing cost [10]. On the other hand, hyperspectral images contains noise because of both scene and sensor related reasons. Since superpixels are oversegmented regions and each superpixel is comprised of contiguous pixels, using the representative of each superpixels reduces the noise effect in the image [10]. Based on these observations, superpixel extraction in hyperspectral image analysis has been employed in different applications. For instance, superpixels are utilized in [11] as a method for using both spectral and spatial information in HSI in order to improve the performance of classification. In another work, [10], superpixels are used as an oversegmentation method to eliminate the noise during endmember detection.

The previous approaches for superpixel extraction methods from hyperspectral images [12],[13] mostly use a direct adaptation of the superpixel methods which are developed for RGB images. For instance, Roscher et al. [12] has applied the widely used superpixel algorithm, SLIC [4], which is proposed for RGB images, for the superpixelization of hyperspectral images. Shanshan et al. [13] has performed modifications on the superpixel algorithm in [4] to oversegment hyperspectral images.

During these adaptations, the mentioned approaches have directly used the same similarity metric, simply the Euclidian distance, used for RGB images to measure the similarity of
the pixels of hyperspectral images. However, considering the multidimensional characteristics of hyperspectral pixels covering many spectral channels, a direct adaptation might not always be the optimal method for the performance of over-segmentation. Such methods might fail to adapt to object boundaries and cause an undersegmentation error [5].

In this paper, we first explore the optimal similarity metric for multidimensional pixels of hyperspectral images for superpixel extraction. We investigate two approaches for similarity detection during superpixel extraction, first comparing the hyperspectral pixels individually, and second, comparing the pixels by using also their neighborhood. The spectral similarity metrics used for investigation are selected as spectral angle mapping (SAM) [1], spectral information divergence (SID) [2] and spatial coherence distance [3] due to their common usage in the hyperspectral literature. Secondly, based on our investigation for the optimal similarity metric selection, we develop a superpixel algorithm in this paper which iteratively updates the boundary of the superpixels. The proposed updating algorithm uses the selected spectral similarity metric to find the distance of the boundary pixels to the superpixels in their neighborhood. The proposed approach is compared with a pioneer state-of-the-art superpixel algorithm, SLIC [4], and its superiority is verified in terms of the superpixelization performance metrics, namely boundary recall and undersegmentation error [5].

The rest of the paper is organized as follows. In Section 2, we outline the main stages of the proposed superpixel algorithm. In Section 3, the performance of the different metrics are compared and the best metric is selected for the employment of the proposed method. Then, the proposed method is compared with the SLIC based hyperspectral superpixel algorithm. Finally, the conclusions are given in Section 4.

2. PROPOSED SUPERPIXEL EXTRACTION METHOD

The mentioned steps of the proposed superpixel algorithm are given in details as follows:

1. Superpixels for a given size are initially extracted from the hyperspectral input image with the assumption that superpixels are distributed uniformly.

2. The boundary pixels of the extracted superpixels are updated such that superpixel boundaries align with the object boundaries. For this purpose,
   
   (a) the coordinates of the pixels in the 8-neighborhood of a boundary pixel $BP_{ij}$, (corresponding to the $j^{th}$ boundary pixel of $i^{th}$ superpixel), are found. The superpixels for each pixel in the 8-neighborhood are identified. These superpixels form the candidate superpixels to assign a boundary pixel during the update.

   (b) An energy function to relate each boundary pixel to the candidate superpixels is calculated (Eqn. 1).

   (c) The boundary pixel is assigned to the superpixel corresponding to the minimum energy value among all superpixel candidates.

3. After all the superpixels are updated, the convexity of the superpixels are computed. From different approaches to compute convexity of a closed curve corresponding to the superpixel boundaries, we use the shift in the centroid position after each update as a measure of convexity as in [8]. The average convexity of all superpixels are used as the stopping criteria.

4. If the stopping criteria is satisfied, the algorithm continues to step 5. If not, it returns to step 2.

5. The extracted superpixels with their index information are given as output.

The energy function between the boundary pixels and candidate superpixels in the given algorithm is defined as the weighted sum of spatial distance and spectral distance between the boundary pixel and representative of the candidate superpixel, which is given as:

$$F_{energy} = \lambda * d_{spatial} + (1 - \lambda) * d_{spectral} \quad (1)$$

where $d_{spatial}$ denotes the spatial distance between the spatial coordinates and $d_{spectral}$ corresponds to the spectral distance between the spectral signatures.

The distance metrics in the given equation are the most important factors during the adaptation of a superpixel algorithm to the multidimensional hyperspectral images. The proposed method selects the Euclidean distance between the spatial coordinates as the spatial distance metric. On the other hand, three metrics are chosen to be used as the spectral distance between the pixels. First, the classical Euclidean distance is utilized. Second, spectral angle mapping (SAM) [1], which gives the angle between two signals, is selected as it provides robustness to the changes in the amplitude of the signal. As a third spectral distance metric, we choose the spectral information divergence (SID) [2]. The performance of the SID metric compared to the other distance metric is tested and verified in [14].

In addition to the mentioned metrics individually measuring the distance between the pixels, we also analyse the performance of the proposed superpixel algorithm when the distance between the hyperspectral pixels are measured by using also their neighborhood [3]. Using the neighbour pixels during the distance measurement not only reduces the dimension of the HSI pixel but also preserves the topological structure of the data [3]. For this purpose, we treat each pixel with its
neighbours by using the spatial coherence local linear embedding (SCLLE) [3]. The distance between a boundary pixel and a superpixel representative is measured as the summation of all the distance between the neighbor pixels of the boundary pixel and the superpixel representative.

![Fig. 1. Visual comparison between SLIC [4] and proposed superpixel algorithm with different distance metrics.](image)

<table>
<thead>
<tr>
<th></th>
<th>SLIC</th>
<th>BU-ED</th>
<th>BU-SAM</th>
<th>BU-SID</th>
<th>BU-SCLLE-ED</th>
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<tr>
<td>Indian Pines</td>
<td>BR 0.7862</td>
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<td>0.9543</td>
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<tr>
<td>Salinas</td>
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<td>0.7176</td>
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<tr>
<td></td>
<td>EU 18.12</td>
<td>20.56</td>
<td>20.26</td>
<td>18.16</td>
<td>19.11</td>
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Table 1. Performance results of SP algorithms

3. EXPERIMENTAL RESULTS

The experiments are conducted on a commonly used hyperspectral data sets, namely Indian Pines and Salinas. The boundary recall (BR) and undersegmentation error (EU) are used as the performance metrics to compare different methods in the tests. The boundary recall refers to the ratio of the extracted superpixel boundaries matching to the object boundaries to the total object boundaries in the image whereas the undersegmentation error corresponds to the accuracy of the correct segmentation of the objects in the image [5].

We compare six cases in the comparisons with respect to the combinations of the selected superpixel method and the distance metric: (1) The proposed boundary update (BU) algorithm + SAM metric, (2) BU algorithm + SID metric, (3) BU algorithm + Euclidean distance (ED), (4) BU algorithm + SCLLE + ED, (5) BU algorithm + SCLLE + SAM, and (6) SLIC algorithm + Euclidean Distance (ED) methods. While the first three cases correspond to the comparison of pixels individually, the fourth and the fifth cases correspond to the comparison of the pixels with their neighborhod. The last is the state-of-the-art SLIC algorithm [4] in the literature which uses Euclidean distance for the similarity metric between the hyperspectral pixels. Figure 2 presents the outputs of the superpixel algorithms for the compared six cases for Pavia image. In each case, different areas can be oversegmented by superpixels; however, it is not easy to compare the performance of the algorithms visually to make a judgment about the boundary recall.

In Table 1, the boundary recall and segmentation error results are given for Pavia and Indian Pines images for the compared six cases. The proposed algorithm performs better than the SLIC based method for all the utilized metrics for Pavia in terms of the boundary recall. The proposed method with the distance metrics ED, SAM and SID gives also better boundary recall results for Indian Pines. However, the metrics using the neighbor relations indicate a lower performance. The undersegmentation error for the proposed method is higher than the SLIC in the tables. Note that the main aim of the proposed algorithm is to track the boundaries effectively more than to split the object into the smaller segments. However, for applications aiming lower segmentation errors, the proposed algorithm can also be adapted conveniently by tuning the initial superpixel size.

Figure 2 illustrates the boundary recall and undersegmentation error with respect to the number of superpixels for Salinas image. Similar results and conclusions are also obtained for the other test images, such as Indian Pines and Pavia, given in the utilized data set. As a first conclusion, the comparison of the 3rd and the 6th cases for the boundary recall results indicates that the proposed BU algorithm with Euclidean distance gives better performance than the SLIC algorithm. This can be explained with the more flexible pixel by pixel treatments of the boundary regions in the proposed method compared to the SLIC algorithm. Secondly, the comparison of the first three cases and the fourth and fifth cases reveals that the proposed BU algorithm gives better results with the similarity metrics which compares two pixels with their neighborhoods. In terms of the undersegmentation error, the proposed method gives the minimum error when the similarity metric between the pixels are compared with their neighborhoods by using the the SAM metric (SCLLE+SAM). This is followed by the individual comparison of the pixels with the SID metric (BU+SID). However, for the case of the Euclidean distance, SLIC seems to give a better performance than the proposed boundary update method. The experiments reveal that when the proposed method is used with the SID metric, it gives a better performance than the SLIC based superpixelization method both in terms of boundary recall and undersegmentation error.

4. CONCLUSIONS

In this paper, we first explore the optimal similarity metric for multidimensional pixels of hyperspectral images for superpixel extraction. We study two approaches for similarity metrics in terms of modeling the hyperspectral pixels. First, hyperspectral pixels are represented as individual pixels and second, each hyperspectral pixel is represented by using its neighbor pixels. Based on our investigation, the proposed
superpixel algorithm outperforms a pioneer state-of-the-art superpixel algorithm, SLIC [4], for boundary recall performance criteria. In addition, among different distance metrics, the distance metric which uses individual pixel representation is better than others.

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6. REFERENCES


