ABSTRACT

Image segmentation is a fundamental stage in several domains of knowledge, in particular, remote sensing applications. Its main purpose is to partition an image into constituent regions of interest through characteristics such as pixel intensity or color, texture, and shape of objects. This work presents a two-stage image segmentation method, allowing an overall computation cost reduction while maintaining an adequate discrimination of details. Initially, wavelet transforms are applied to image blocks to extract a number of features and identify homogeneous regions. Then, Euclidean distance and partial least squares classifiers are evaluated for effectiveness on the second stage of the method.

KEYWORDS: image segmentation, wavelet transforms, partial least squares.
features are extracted to model distinct classes of an image and produce a first rough segmentation. The features are obtained from the subbands of a wavelet transform applied to each block. Two dimensional wavelet transforms usually produce one low-frequency subband (LL) and three high-frequency subbands (LL, LH, HL). A hierarchy of subbands can be generated by further decompositions of the resulting LL subbands [5]. As wavelet coefficients in different frequency bands show variations in horizontal, vertical and diagonal directions, it has been shown that texture features can be extracted from these coefficients [6].

A well known feature based on wavelet coefficients is the energy, shown in Equation 1, where \( sb \) denotes a particular \( m \times m \) element subband and \( c(x, y) \) represents wavelet transform coefficients in the coordinates \( (x, y) \) of the subband.

\[
E_{sb} = \sqrt{\frac{1}{m^2} \sum c(x, y)^2}
\]  

(1)

In addition to energy, the use of statistical measures is also common, such as standard deviation. The smoothness, expressed in Equation 2, assumes the value zero when the coefficients of a region are constant (smooth) and increases to one as the variance \( \sigma_{sb}^2 \) of subband \( sb \) becomes greater in rough regions.

\[
E_{sb} = 1 - \frac{1}{1 + \sigma_{sb}^2}
\]  

(2)

For each image block, energy, standard deviation and smoothness features are calculated for the subbands of the wavelet transform. In color images, the feature extraction process is applied to each band of the YCbCr color model. The k-means clustering algorithm is then used to group the feature vectors (blocks) into a set of classes.

To reduce the blockiness effect, blocks located at boundaries are detected based on the similarity to the blocks in their class. The resulting measurement ranges from \(-1\) to \(1\), indicating low to high similarity. The measure for a block \( b \) is defined in Equation 3, where \( D(b, c) \) is the mean distance from block \( b \) to the blocks of class \( c \), and \( d(b) \) is the mean distance from block \( b \) and the blocks of its own class.

\[
\text{Sim}(b) = \frac{\min (D(b, c), 2) - d(b)}{\max (\min (D(b, c), 2), d(b))}
\]  

(3)

The inequality \(|\text{Sim}(b) - \mu_b| > t \sigma_b\) is then calculated, where \( t \) is a real value, \( \mu_b \) and \( \sigma_b \) are respectively the mean and standard deviation of the similarities of \( b \) and the samples in its class. If the inequality is true, the block is marked as heterogeneous and its segmentation will be refined in the final stage of the method.

FINAL SEGMENTATION

The final segmentation is a pixelwise stage to determine the class of the pixels remaining from the first stage. It is accomplished by using the partial least squares method, which estimates new predictor variables (latent variables) as a linear combination of the original variables, defined in matrix \( X \) composed of predictors (feature vectors of the homogeneous blocks identified in the first stage of the segmentation), and vector \( y \) with response variable (class labels assigned by k-means clustering method in the first stage). A detailed discussion of PLS can be found in [3, 4].

A one-against-all scheme is used to learn a PLS discriminatory model. Each remaining pixel is assigned to that class which presents the highest regression response [4].

RESULTS AND DISCUSSION

The proposed image segmentation method using PLS was compared to the previous work presented in [7], which used Euclidean distance in the second stage of the method. The used block
sizes were $4 \times 4$ and $8 \times 8$ pixels. Wavelet transforms were applied using Symlets-2 filters with two levels of decomposition. Heterogeneous blocks that required further segmentation were identified with $t = 0.75$ in Equation 3. Table 1 presents some test images along with their dimensions and percentage of segmented pixels in the final stage. Since the refinement step is applied only to a smaller portion of the image, computational cost is significantly reduced.

Table 1: Test images and percentage of heterogeneous pixels in the final segmentation.

<table>
<thead>
<tr>
<th>Images</th>
<th>Dimensions (pixels)</th>
<th>Segmented Pixels in Final Stage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shark Bay</td>
<td>$420 \times 420$</td>
<td>14.63</td>
</tr>
<tr>
<td>Moreno Glacier</td>
<td>$340 \times 340$</td>
<td>20.75</td>
</tr>
<tr>
<td>Chesapeake Bay</td>
<td>$512 \times 512$</td>
<td>13.67</td>
</tr>
<tr>
<td>Forest and Sand</td>
<td>$512 \times 512$</td>
<td>5.85</td>
</tr>
<tr>
<td>Palm Island</td>
<td>$512 \times 512$</td>
<td>14.81</td>
</tr>
</tbody>
</table>

To evaluate the effectiveness of PLS compared to the previous approach [7], accuracy and kappa coefficient [8] of the resulting segmentation were computed based on manually annotated ground truth images. Table 2 shows that the proposed method produced superior segmentation results for some images.

Table 2: Comparison between second stage with Euclidean distance and PLS.

<table>
<thead>
<tr>
<th>Images</th>
<th>Euclidean accuracy</th>
<th>Euclidean (\kappa) coefficient</th>
<th>PLS accuracy</th>
<th>PLS (\kappa) coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shark Bay</td>
<td>0.970</td>
<td>0.930</td>
<td>0.972</td>
<td>0.934</td>
</tr>
<tr>
<td>Moreno Glacier</td>
<td>0.848</td>
<td>0.753</td>
<td>0.944</td>
<td>0.878</td>
</tr>
<tr>
<td>Chesapeake Bay</td>
<td>0.934</td>
<td>0.859</td>
<td>0.987</td>
<td>0.974</td>
</tr>
<tr>
<td>Forest and Sand</td>
<td>0.988</td>
<td>0.975</td>
<td>0.931</td>
<td>0.854</td>
</tr>
<tr>
<td>Palm Island</td>
<td>0.909</td>
<td>0.806</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Due to space limitations, Figure 1 illustrates three results obtained with the methods based on Euclidean distance and partial least squares. Both methods preserved small and thin details, such as those present in Chesapeake Bay and Palm Island images. PLS-based image segmentation produced superior results, for instance, in land regions located at the lower right of the Chesapeake Bay image. However, it mis-segmented some parts of Moreno Glacier image. This fact is probably due to the reduced block size used in the experiments. Generally speaking, it can be observed that the method worked well in distinguishing regions of the images and it is suitable for remote sensing applications.

CONCLUSIONS

This paper described a segmentation method of color textured remote sensing images based on wavelet transforms and partial least squares method. The use of partial least squares represented an improvement on the segmentation results when compared to a previous approach [7]. As future investigation, different block sizes will be tested to demonstrate the effectiveness of the PLS-based image segmentation.

ACKNOWLEDGEMENTS

The authors would like to thank the Image Analysis Laboratory at NASA Johnson Space Center, as well FAPESP, CNPq and CAPES for the financial support.
Figure 1: Segmentation results for three remote sensing images.

REFERENCES


