A first step towards a detector of ceramic roofs

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Abstract. This article presents the first results of an image processing operator for ceramic roofs detection, developed for the InterIMAGE system. The driving idea is to form hypothesis based on predefined information of roofs, in a model stored as decision tree. The model was defined by a supervised strategy, starting from segmenting different urban images of high spatial resolution, followed by extracting several features from the segments. The feature selection and the definition of thresholds used the data mining algorithm of decision trees, based on entropy maximization. Finally, the operator classifies new segments and create hypothesis of ceramic roofs according to the model.

Keywords: remote sensing, pattern recognition, roof detection .

1. Introduction

An important application of high spatial resolution satellite images is urban mapping. According to Novack (2009), urban planning regulates and monitors our cities, since their fast growth presents bad outcomes. Araujo (2006) defines *ceramic roofs* as a class of high occurrence in urban imagery. The author characterizes a ceramic roof with simple and rectangular shape, high color variability, but easily identifiable by manual inspection. However, image processing algorithms must go after the automatic detection of roofs in remote sensing images.

Recently, image processing and GIS started to grow together in the so called *object based image analysis* – OBIA (BLASCHKE, 2010). This research area deals with classifying segments. Segments are regions formed by some homogeneity criteria, in one or more dimensions. OBIA takes advantage of spectral information contained in the objects, like mean values per band, median values, amplitude, and variance. It is possible to relate geometric information and neighborhood relations between segments as well.

However, only a few OBIA systems are available for researchers. Costa et al. (2010) describes InterIMAGE, a knowledge-based software for image interpretation. The system couples segmentation with specialized image processing operators, created to aid users to define targets in remote sensing images. Beside segmentation and image processing operators, it is possible to insert rules manually for classification, based on analyst experience and the segments properties.

This article presents our first effort in developing an image processing operator for InterIMAGE, designed to detect ceramic roofs on remote sensing images of high spatial resolution. In the next section we define the employed method to detect roofs in high resolution images. Section 3 presents some results, and we finish in section 4.

2. Methodology

The proposed method aims to find a generalist model of ceramic roofs. We aim to apply the model in similar high resolution images of urban scenes, since according to (WOODCOCK; STRAHLER, 1987) the suitable scale for observations is a function of the environment and the information wanted. We created the model using the algorithm of decision trees based on Quinlan (1993), and a reference set of Brazilian urban images, with different regions and sensors. We define the outline to set up the model as follows:

- Obtain urban high spatial resolution imagery, with different sensors. These images compose the reference set.
- Segment each image using the multiresolution algorithm based on Baatz e Schape (2000).
- Perform extraction of spatial and spectral features from the segmentation objects.
- Normalize the features using *z-score* technique (VESANTO, 2002), which subtracts the averages and divide the feature values by their standard deviations. This normalization aims to remove the influence of different sensor properties.
- Select and label all representative samples from every image of class *ceramic roofs*, and label the remaining objects as *background*.
- Merge normalized training data into a reference set.
- Perform classification using decision trees algorithm.
- Interpret manually the resultant decision tree to build the final model for ceramic roof detection.

2.1. Reference segmentation

We used different imagery to build a generalist model. Figure 1 shows the different scenes used as reference for the model. One must realize that all images contain similar spatial resolution, which limits the model for this resolution. As we know that different sensors hold different spectral ranges, we used only the visible channels, coupled with spatial features available at InterIMAGE.

Figure 1: Input images used to define ceramic roofs model.

The segmentation were tuned to be the most proper to describe the objects of interest, *i.e.* ceramic roofs, without subsegmentation; meanwhile oversegmentation was expected. According to the algorithm described in Baatz e Schape (2000), we employed the scale of 20, the compactness of 50%, and the color factor of 50% for all images. Figure 2 shows the resultant segmentations.

Figure 2: Results of segmentation applied to images from Figure 1.

2.2. Feature selection

The final model was used in the roof detector operator. The input is a set of segments and their features. Applying the decision tree for the features, the algorithm decides whether the segment is a ceramic roof or not. The model chose features both spatial (e.g., area, elliptic fit, length, perimeter, rectangular fit, and width) and spectral (e.g., amplitude, entropy, mean, mode, standard deviation, sum, and ratio of pixels). Such features are described below:

Area is the area of the segment, in number of pixels.

Elliptic fit finds the best ellipse which fits outside the segment and returns the ratio between the segment area and the ellipse area.

Length is the height of the segment bounding box.

Perimeter considers the number of pixels in the border of the segment.

Rectangular fit finds the best rectangle which fits outside the segment and returns the ratio between the segment area and the rectangle area.

Width is the width of the segment bounding box.

Amplitude means the maximum pixel value minus the minimum pixel value.

Entropy is a texture feature that measures the randomness of the pixel distribution.

Mean is the average value for all pixels.

Mode is the pixel value that occurs the most often inside a segment.

Ratio is the weighted average of the pixel values for each spectral channel.

Table 1: Confusion matrices for the reference set. The reference data are displayed in the rows. Class 0 is background, and 1 is ceramic roofs.

```
       0     1
---------------
 0 | 2346   27
 1 |   10  144

kappa: 0.878
```

```
       0    1
-------------
 0 | 223    0
 1 |  22   97

kappa: 0.851
```

```
       0    1
-------------
 0 | 976   34
 1 |  19  221

kappa: 0.866
```

```
       0     1
---------------
 0 | 3284   58
 1 |   38  306

kappa: 0.850
```

```
       0     1
---------------
 0 | 2320   15
 1 |   37  278

kappa: 0.903
```

```
       0     1
---------------
 0 | 1490   18
 1 |   70  275

kappa: 0.833
```

```
       0     1
---------------
 0 | 1209   39
 1 |    4  187

kappa: 0.879
```

```
       0     1
---------------
 0 | 1040    9
 1 |   15  141

kappa: 0.910
```

Standard deviation is the standard deviation of pixels values inside the segment.

Sum is the sum of all pixels values inside the segment.

3. Results

In this section we evaluate the proposed model by applying our technique into different images. The first experiment employed the roof detection into the images used to build the model, *i.e.* the reference set. The second experiment applied the model into the test set, different images not used to create the model. If the model were generalist enough to turnout good results in the second experiment, we are able to define a generalist detector of ceramic roofs, applied to high resolution imagery of urban scenes in Brazil.

We expected the model was able to merge the training samples from the images and obtain accurate classification for the first experiment. However, according to Webb (2002), achieving best performance on the reference set is not required, since it may be possible to achieve 100% classification accuracy on the reference but the generalization performance is poor. Therefore, choosing the right model is a hardworking task. Correct rates for the reference images varied between 93.56% and 98.53%, with an average kappa of 0.871. Table 1 shows the confusion matrices.

The second experiment used test images displayed in Figure 3. They were segmented with the same parameters as the reference images, and the same features were extracted. The full classified images are displayed in Figure 4.

According to Lunetta et al. (1991), the overall accuracy is the simplest descriptive statistic, and with the error matrix can be used as a starting point for more complex measurements. We calculated the percentage of hits in the class of ceramic roofs. In the 4 images, we got the values of 94.73%, 77.55%, 70.83%, and 94.94%. Table 2 presents the confusion matrices for the test experiments.

InterIMAGE interpretation model is based on a tree, where the topmost nodes produce more generalist hypothesis, and the bottommost nodes are more specific. We propose our method as a generalist detection of ceramic roofs, leaving for the more specific nodes to approve or reject

Figure 3: Test images used to evaluate the generalist model of ceramic roofs.

Figure 4: Roof detection in test images (showing full images).

Table 2: Confusion matrices for the test set. The reference data are displayed in the rows. Class 0 is background, and 1 is ceramic roofs.

	0	1
0	629	14
1	1	18

kappa: 0.694

	0	1
0	164	10
1	11	38

kappa: 0.723

	0	1
0	382	1
1	7	17

kappa: 0.799

	0	1
0	2527	151
1	10	188

kappa: 0.671

the hypothesis. We suggest that since our commission errors are not high, and the omission errors can have medium values (see Tables 1 and 2).

4. Conclusion

This article presented a first research towards a ceramic roof model for remote sensing images with high spatial resolution. We pointed the necessary steps to build the model using a decision tree algorithm based in Quinlan (1993), and applied it to a roof detector operator for InterIMAGE. Preliminary results showed encouraging results, with averages of 84.51% of hits, and 0.721 for kappa values. However, a refinement of the model is necessary to be more robust.

Further research includes an adaptable learning strategy, where the expert selects misclassified objects, updating the model for further analysis. Another improvement in the algorithm is the use of fuzzy decision trees, that outputs likelihoods of a segment to belong to a certain class (OLARU, 2003).

The resultant operator is being coded using free GIS and Image Processing C++ library called TerraLib (CAMARA et al., 2008). More information about InterIMAGE operators are available at `http://www.dpi.inpe.br/terraaida`.

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