Satellite Image Segmentation Using Wavelet Transforms Based on Color and Texture Features

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Abstract. Image segmentation is a fundamental process in remote sensing applications, whose main purpose is to allow a meaningful discrimination among constituent regions of interest. This work presents a novel image segmentation method based on wavelet transforms for extracting a number of color and texture features from the images. Traditional feature extraction techniques based on individual pixels usually demand high computational cost. To reduce such computational cost, while achieving high-quality results, our approach is composed of two main stages. Initially, the image is decomposed into blocks of pixels and a wavelet transform is applied to each block to identify homogeneous regions of the image, assigning the entire block to a class. A refinement stage is applied to the remaining pixels which belong to blocks marked as heterogenous in the first stage. The developed method, tested on several remote sensing images and compared to a well known image segmentation method, presents high adaptability to image regions.

1 Introduction

Image segmentation is a crucial operation in many computer vision and image interpretation systems, with applications in a variety of scientific and industrial fields, such as medicine, remote sensing, microscopy, content-based image and video retrieval, document analysis, industrial automation and quality control.

The segmentation process consists of partitioning an image into a set of regions with similar features, which can be used to assist in subsequent recognition and analysis tasks. The most common features used in image segmentation include texture, shape, gray level intensity and color. Although several segmentation approaches have been proposed in the last decades, there have been only few methods combining such features.

Image segmentation algorithms are commonly categorized into supervised or unsupervised [1]. The first one requires prior knowledge on the type or number of patterns (classes) present in the image, whereas the second automatically searches for groupings with similarities in the image based only on the information extracted from the data. Several recent techniques have been proposed for image segmentation using region growing [2], graph cuts [3, 4], normalized cuts [5] and Markov random fields [6].

This work presents a novel image segmentation method based on wavelet transforms for extracting a number of color and texture features from the images. Our method, which does not use any training data, is divided into two stages. First, features are extracted from the wavelets coefficients from small regions of the image. Then, the regions are grouped into a set of classes using k-means clustering algorithm. Finally, a pixelwise segmentation is applied to those pixels which were not segmented in the first stage.

By using this two-step process, it is possible to reduce the computational cost significantly, since only a small number of pixels needs to be segmented in the second stage, avoiding the feature calculation for every pixel in the image. Furthermore, the parameters computed from the regions present in the image during the first stage are used to refine the segmentation process in the second stage.

Although the combination of texture and color is not frequently used, it provides a high discriminative power of regions present in the image. This work extracts texture features from color images using wavelet coefficients. The images are represented in the YCbCr color space.

This paper is organized as follows. Section 2 describes the extraction of texture and color features used to obtain the final image segmentation. In Section 3, the proposed method is presented and discussed. Experimental results obtained by applying the proposed method are shown in Section 4. Finally, Section 5 concludes with some final remarks.

2 Color and Texture Feature Extraction

The use of color plays a significant role in the image analysis process performed not only by human beings, but by computer systems as well. Many techniques for feature extraction are based on the color image histogram [7, 8]. The histograms are invariant with respect to image translation and rotation, being also invariant under scaling through its normalization. However, the color histograms do not incorporate spatial information of pixels in the image.

The model used to represent color in images can also affect the segmentation performance. Several models have been proposed for image processing systems using color images [9], such as RGB, CMY, HSV, YUV, YIQ and YCbCr. Although RGB and CMY are models widely used in color display and printing, respectively, the intensity and color components are correlated in these models. On the other hand, models such as YCbCr and HSV are suitable for certain applications since the intensity (luminance) and color information (chrominance) are better related to human visual perception, allowing to exploit color properties more conveniently.

Texture can be defined as a repetitive arrangement of patterns over a region. It can also be characterized by local variations of pixel values that repeat in a regular or random pattern on the object or image. Although the human visual system presents relative capability for texture description and recognition, the proposition of texture descriptors is not a simple task. Such difficulty is reflected by the great amount of definitions and methods encountered in literature [10–13].

The main texture feature extraction methods can be categorized into structural, statistical and spectral [14]. Structural methods are based on an arrangement of textural elements. Statistical methods define textures as stochastic processes and characterize them by a number of statistical measures. The most important statistical approaches include co-occurrence matrices, autocorrelation methods, and Markov random field. Spectral approaches focus on periodic patterns resulting in peaks in the frequency domain, such as Gabor filtering and wavelet decomposition.

Wavelet transform decomposes a signal by means of a series of elementary functions, created from dilations and translations of a basis function ψ, known as *mother wavelet*. The basis functions of a discrete wavelet transform, $\psi_{j,k}(t)$, of time independent variable t, can be expressed as

$$\psi_{j,k}(t) = 2^{-j/2}\ \psi(2^{-j}t - k) \tag{1}$$

where j and k are integers that guide the dilations and translations of the function ψ to generate a family of wavelets, such as Haar and Daubechies [15, 16].

Wavelet transforms can be implemented by using a pair of lowpass and highpass filters, called *quadrature mirror filters* (QMF), represented by a sequence of coefficients [16, 17]. In a 2D wavelet decomposition, the filters are applied to an image in both horizontal and vertical directions, followed by a downsampling. The output of each level will generate four subband images, LL, LH, HL and HH. The same process can be repeated on the LL image to generate the next decomposition level.

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 [18].

The image analysis process normally uses a representative scheme of the image or its components (objects or pixels), known as *feature vector*. In our approach, such a vector is composed of numerical features described in the remaining of this section.

A well known feature based on wavelet coefficients is the *energy*, shown in Equation 2, where sb denotes the LL, LH, HL and HH subbands, $c(x, y)$ represents wavelet transform coefficients in the coordinates (x, y) for each one of these subbands containing $m \times m$ pixels. Wavelet energy reflects the distribution of energy along the frequency axis over scale and orientation and have proven to be very useful for texture characterization.

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

The energy is similar to the L^N-norms which are given by

$$L_{sb}^{N} = \sqrt[N]{\sum |c(x,y)|^N} \tag{3}$$

In addition to energy and norm feature, the use of statistical measures such as mean, median and standard deviation can also be used.

3 Segmentation Method

The developed image segmentation method is composed of two stages, as can be seen in Figure 1. The purpose of this division in stages is to reduce computational cost, such that an initial segmentation is applied to square blocks of pixels whereas a refinement step segments the remaining pixels avoiding blockyness effect at region boundaries.

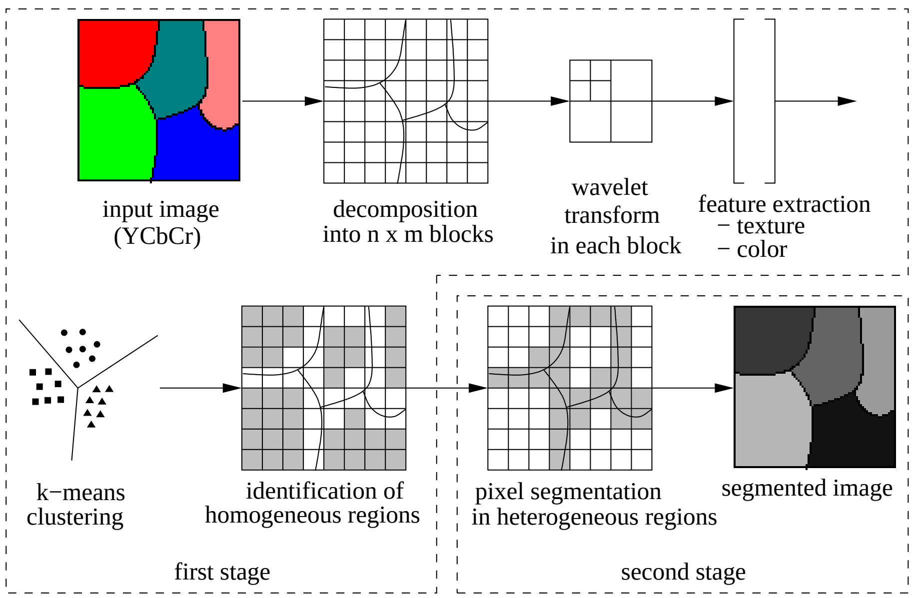


Fig. 1: Diagram of the proposed segmentation method

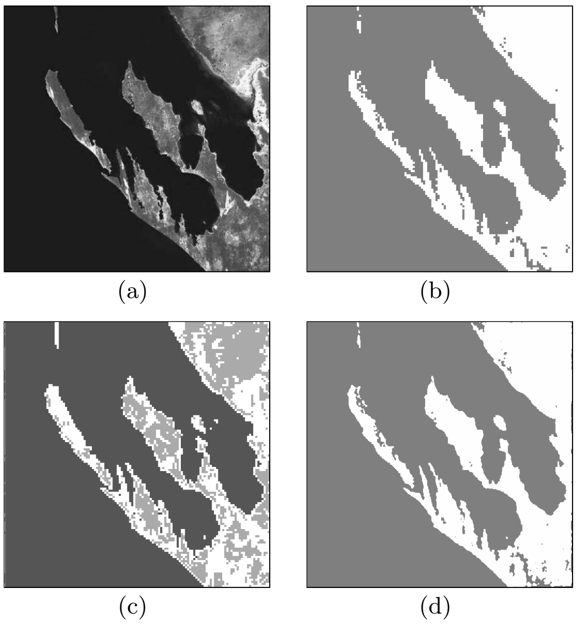
The initial segmentation identifies blocks with similar features, grouping them into corresponding classes. Heterogeneous regions, for instance blocks located in frontiers between different regions, are detected and more precisely segmented in the second stage.

3.1 Initial Segmentation

The initial segmentation partitions the input image into square blocks with $m \times m$ pixels, then applies a wavelet transform to each block to extract features to compose a feature vector. The k-means clustering algorithm is then used to group the feature vectors into a set of classes [19].

For each image block, the features described in Section 2 for the LL, LH, HL and HH subbands are calculated in each color channel (Y, Cb and Cr) of the image. Therefore, blocks are represented by a feature vector composed with measures extracted from the subbands of the wavelet transform.

To reduce the blockyness effect present at the boundaries between regions, as exemplified in Figure 2(c), the blocks located in these regions are detected and marked to be segmented in the final stage of the method. The identification of blocks that require further segmentation is based on the similarity between such blocks and their adjacent regions. If the feature vectors are distant enough so that the distance between them is more than a threshold T, the block is marked as heterogeneous and its segmentation will be refined at the final stage of the method.



(a) (b) (c) (d)

Fig. 2: Shark Bay, Australia. (a) original image; (b) after initial segmentation; (c) detection of boundary regions (white regions are marked to be considered in the second stage); (d) final segmentation

3.2 Final Segmentation

The final segmentation is a pixelwise stage to determine which class each remaining pixel belongs to. A window centered at each pixel left to this stage is used to calculate the feature vector. Similarly to the first segmentation step, the features extracted from each subband in the wavelet domain are used to measure the similarity between classes.

Finally, the Euclidean distance between the feature vectors for the pixel under consideration and the parameters (i.e. centroids obtained by k-means algorithm) for all classes are compared, such that each pixel is assigned to the class whose distance is minimum.

4 Experimental Results

To select suitable wavelet basis functions and features to be used in the segmentation of real images, a set of wavelets and features was firstly experimented on synthetic mosaic images. The mosaics were constructed with textures from the Vision Texture database [20]. Each mosaic of 512×512 pixels was built as blocks of texture with 64×64 pixels. For a particular block, both the texture and its extracted subregion were chosen randomly.

Initially, wavelet families such as Daubechies, Coiflets, Symlets and Biorthogonal were tested with the following features: energy (e2), L^1-norm (n1), mean (m1), median (m2) and standard deviation (std).

Based on the best results from the previous test, a subset of wavelets and features was chosen to be used on the real images. According to the conducted experiments, energy and standard deviation separately produced the best results, whereas mean and median did not yield good outcomes. Therefore, energy and standard deviation were chosen as measures to compose the feature vectors. The selected wavelet bases among the best results were Haar, Daubechies-2, Symlet-2, Coiflet-2 and Biorthogonal-4.4.

Table 1 shows the percentage of correct segmentation obtained by comparing the outcome of the algorithm and the ground truth of the mosaic in Figure 3. Since the purpose was to find the most prominent parameters for the method, the values shown in the table correspond to a blockwise segmentation as the one described in the first stage of the algorithm, that is, without the final stage refinement.

Our image segmentation method was compared with the technique of normalized cuts developed by Shi and Malik [5]. All images were processed by using the optimal parameters given by the authors. Table 2 shows the accuracy and kappa coefficient [21] for our method and the method proposed by [5]. To obtain the results, the ground truth for the correct segmentation was manually annotated.

Figure 4 shows some results obtained with the proposed method. A large set of remote sensing images was used to demonstrate the effectiveness of the proposed segmentation method. The images were tested with variations of wavelets

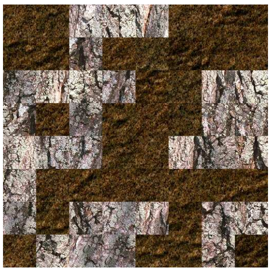


Fig. 3: Example of a mosaic

Table 1: Percentage of correct segmentation of mosaic shown in Figure 3 using block size of 32 x 32 pixels

subband	wavelet	e2	std	e2 and std
LH HL HH	haar	95.3	95.3	95.3
	db2	95.3	95.3	95.3
	sym2	95.3	95.3	95.3
	coif2	96.0	96.0	96.0
	bior4.4	95.7	95.7	95.7
LL LH HL HH	haar	98.4	96.4	97.6
	db2	98.0	96.8	97.6
	sym2	98.0	96.8	97.6
	coif2	98.0	96.8	98.0
	bior4.4	98.0	96.8	98.4

Table 2: Comparison between developed method and segmentation method proposed by Shi and Malik [5]

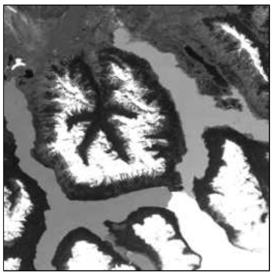
Images	our method		Shi and Malik	
	accuracy	κ coefficient	accuracy	κ coefficient
Shark Bay	**0.975**	**0.939**	0.580	0.152
Moreno Glacier	**0.856**	**0.766**	0.474	0.105
Chesapeake Bay	**0.933**	**0.857**	0.865	0.722
Forest and Sand	**0.986**	0.973	0.969	**0.985**
Palm Island	**0.915**	**0.817**	0.511	0.088

and block sizes to allow a detailed evaluation of the method in terms of adaptability to the regions present in the input images.

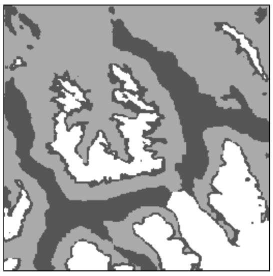
From the results, it can be observed that the proposed method works well in distinguishing regions on images. Our method is suitable for remote sensing applications since it is capable of preserving details and properly deals with regions possessing a small area of the image, such as those present in Chesapeake Bay and Palm Island images.

Table 3: Results using developed method

Images	Dimensions (pixels)	Segmented Pixels in Final Stage (%)
Shark Bay	420×420	16.99
Moreno Glacier	340×340	39.52
Chesapeake Bay	512×512	21.36
Forest and Sand	512×512	27.92
Palm Island	512×512	6.15



(a) Moreno Glacier, Argentina (db1, block size of 4×4 pixels, 3 classes)



(b) segmentation with proposed method

(c) segmentation with normalized cuts

(d) Chesapeake Bay (db2, block size of 8×8 pixels, 2 classes)

(e) segmentation with proposed method

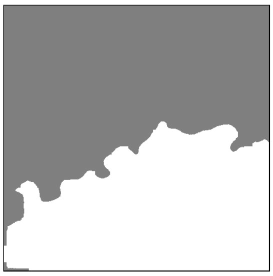
(f) segmentation with normalized cuts

Fig. 4: Results for a set of images

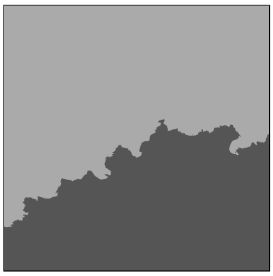
Table 3 presents image dimensions and percentage of segmented pixels in the final stage. Since the refinement step is applied only to a smaller portion of the image, computational cost is significantly reduced. Heterogeneous blocks that required further segmentation were identified between the two closer feature vectors with threshold $T = 0.1$.

The block size is an important parameter for the preservation of details and good identification of regions. The smaller the block, the best the detail identification. Nonetheless, the choice of larger blocks may result in better region description.

(g) Forest and sand (db2, block size of 16×16 pixels, 2 classes)



(h) segmentation with proposed method



(i) segmentation with normalized cuts

(j) Palm Island, United Arab Emirates (sym2, block size of 8×8 pixels, 2 classes)

(k) segmentation with proposed method

(l) segmentation with normalized cuts

Fig. 4: Results for a set of images (continued)

5 Conclusions and Future Work

This paper presented a segmentation method of color textured remote sensing images based on a set of features extracted by wavelet transforms using the YCbCr color space. The method is composed of two main steps, a blockwise and a pixelwise stage. The latter one is applied only to a reduced number of pixels, therefore reducing the computational cost.

The proposed method does not use any training data, demanding minimum human intervention with high reliability. An extension of the method to several bands in satellite imagery is planned as future work.

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References

1. Duda, R.O., Hart, P.E., Stork, D.G.: Pattern Classification. 2 edn. Wiley-Interscience (2000)
2. Deng, Y., , S.Manjunath, B.: Unsupervised segmentation of color-texture regions in images and video. IEEE Transactions on Pattern Analysis and Machine Intelligence **23** (2001) 800–810
3. Boykov, Y., Funka-Lea, G.: Graph Cuts and Efficient N-D Image Segmentation. International Journal of Computer Vision **70** (2006) 109–131
4. Rother, C., Kolmogorov, V., Blake, A.: GrabCut: Interactive Foreground Extraction using Iterated Graph Cuts. ACM Transactions on Graphics **23** (2004) 309–314
5. Shi, J., Malik, J.: Normalized Cuts and Image Segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence **22** (2000)
6. Schwartz, W.R., Pedrini, H.: Color Textured Image Segmentation Based on Spatial Dependence Using 3D Co-occurrence Matrices and Markov Random Fields. In: 15th International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision, Plzen, Czech Republic (2007) 81–87
7. Cheng, Y.C., Chen, S.Y.: Image Classification Using Color, Texture and Regions. Image and Vision Computing **21** (2003) 759–776
8. Liapis, S., Sifakis, E., Tziritas, G.: Colour and Texture Segmentation Using Wavelet Frame Analysis, Deterministic Relaxation, and Fast Marching Algorithms. Journal of Visual Communication and Image Representation **15** (2004) 1–26
9. Russ, J.C.: The Image Processing Handbook. CRC Press and IEEE Press, Boca Raton, FL, USA (1998)
10. Arivazhagan, S., Ganesan, L.: Texture Classification Using Wavelet Transform. Pattern Recognition Letters **24** (2003) 1513–1521
11. Idrissa, M., Acheroy, M.: Texture Classification Using Gabor Filters. Pattern Recognition Letters **23** (2002) 1095–1102
12. Singh, M., Singh, S.: Spatial Texture Analysis: A Comparative Study. In: International Conference on Pattern Recognition. Volume 1. (2002) 676–679
13. Sun, J., Gu, D., Zhang, S., Chen, Y.: Hidden Markov Bayesian Texture Segmentation Using Complex Wavelet Transform. In: IEE Proceedings on Vision, Image and Signal Processing. Volume 151. (2004) 215–223
14. Palm, C.: Color Texture Classification by Integrative Co-occurrence Matrices. Pattern Recognition **37** (2004) 965–976
15. Daubechies, I.: Ten Lectures on Wavelets. CBMS-NSF Reg. Conf. Series in Applied Math. SIAM (1992)
16. Mallat, S.G.: A Theory for Multiresolution Signal Decomposition: the Wavelet Representation. IEEE Transactions on Pattern Analysis and Machine Intelligence **11** (1989) 674–693
17. Pun, C.M.: Rotation-invariant texture feature for image retrieval. Computer Vision and Image Understanding **89** (2003) 24–43
18. Unser, M.: Texture Classification and Segmentation Using Wavelet Frames. IEEE Transactions on Image Processing **4** (1995) 1459–1560
19. Gose, E., Johnsonbaugh, R., Jost, S.: Pattern Recognition and Image Analysis. Prentice-Hall, Inc., Upper Saddle River, NJ, USA (1996)
20. VisTex: Vision Texture Database (2008) `http://vismod.media.mit.edu/vismod/imagery/VisionTexture/distribution.html`.
21. Liu, C., Frazier, P., Kumar, L.: Comparative Assessment of the Measures of Thematic Classification Accuracy. Remote Sensing of Environment **107** (2007) 606–616