EXTINCTION PROFILES: A NOVEL APPROACH FOR THE ANALYSIS OF REMOTE SENSING DATA

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ABSTRACT

This paper presents a novel approach named extinction profiles to model the spatial information of remote sensing images. Then, the output of the extinction profile is fed to a grid-search random forest classification method. Results indicate that the proposed approach can effectively extract spatial information from remote sensing gray scale images and provide high classification accuracies in an automatic way.

Index Terms— Extinction Profile, Random Forest Classification, Remote Sensing Data

1. INTRODUCTION

It is now well-known that the consideration of spatial information into classification systems can be highly beneficial in terms of classification accuracies, and the quality of the final classification map [1].

In 2001, Pesaresi and Benediktsson used morphological transformations to build a so-called morphological profile (MP) [2]. Since then, MP has been used intensively for the classification of remote sensing data. However, the concept of MPs suffers from some shortcomings such as (i) the shape of SEs is fixed and (ii) SEs are not able to characterize information related to the gray-level characteristics of the regions. To address such shortcomings, the concept of attribute profiles (APs) was introduced in 2010 [3]. A comprehensive survey on APs and its capabilities for the classification of remote sensing data can be found in [4, 1].

Extinction filters are based on the concept of extinction values [5], which are a powerful tool to measure the persistence of an increasing attribute[1], and are useful to discern relevant from irrelevant extrema in the image. Souza et al. showed that extinction filters are better than attribute filters with respect to simplification for recognition [6], since it preserves more regions and correspondences found by affine region detectors. In addition, in order to solve the issue of manual adjusting threshold values in conventional APs [7], a novel automatic approach is also proposed in this paper to adjust filtering parameters based on the number of extrema.

In this paper, a novel approach, named extinction profile (EP), is proposed for information extraction from remote sensing data. It should be noted that this concept is being used for the first time in the remote sensing community. This approach simultaneously discards unimportant spatial details and preserve the geometrical characteristics of the other regions. Also, the approach is extrema oriented instead of threshold oriented as APs, making it less sensitive to image resolution and it can be set automatically. The EP features are fed to a random forest (RF) classifier and results are compared with AP in terms of classification accuracies. Both AP and EP are applied on two well-known panchromatic data sets captured over Rome and Reykjavik.

The rest of the paper is organized as follows: Section 2 introduces the methodology of the paper. Section 3 is devoted to experimental results. The main concluding remarks are mentioned in Section 4.

2. EXTINCTION PROFILES

2.1. Extinction values

The extinction value of a regional maximum for any crescent attribute is the maximal size of an attribute filter such that this maximum still exists after the filtering. The formal definition of extinction value is the following: consider M a regional maximum of an image f, and $\Psi = (\psi_\lambda)_\lambda$ is a family of decreasing connected anti-extensive transformations[2]. The ex-

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[1]As a reminder: a transformation is known as increasing if and only if it keeps the ordering relation between images f and g, which can be mathematically shown as $f \leq g \quad \Leftrightarrow \quad \psi(f) \leq \psi(g)\ \forall f, g$ where ψ represents the transformation.

[2]As a reminder, a transformation ψ is extensive or a thickening operator if, for each pixel, the transformation output is greater than or equal to the original image, which can be mathematically described as $f \leq \psi(f)$. Anti-extensive or thinning operators have the dual meaning.

tinction value corresponding to M with respect to Ψ and denoted by $\varepsilon_{\Psi}(M)$ is the maximal threshold value λ, such that M still is a regional maxima of $\psi_{\lambda}(f)$. This definition can be expressed through the following equation:

$$\varepsilon_{\Psi}(M) = sup\{\lambda \geq 0 | \forall \mu \leq \lambda, M \subset Max(\psi_{\mu}(f))\}, \quad (1)$$

where $Max(\psi_{\mu}(f))$ is the set containing all the regional maxima of $\psi_{\mu}(f)$. Extinction values of regional minima can be defined similarly. An efficient algorithm for computing extinction values from the max-tree is presented in [8].

2.2. Extinction Filters

The Extinction filter is a connected filter that preserves the relevant extrema of the image based on a connectivity rule (4- and 8-connected are the most common connectivity rules used for 2D images, where a pixel is said to be adjacent to four or eight of its neighboring pixels, respectively). Extinction filters applied on the min-tree is a thickening operator and applied to the max-tree is a thinning operator.

The filter has one parameter: the number n of extrema (maxima or minima) to be preserved. The Extinction filter operation can be done efficiently in the max-tree structure [9]. We choose the n leaves with highest extinction values concerning the attribute being analyzed. The nodes in the paths from these leaves to the root are marked as to be kept. All other nodes are pruned. The main differences between extinction filters and attribute filters is that extinction filters are extrema oriented, i.e. the filter sets the number of extrema, also they preserve the height of the extrema kept.

2.3. Extinction Profiles

EPs are built by stacking a sequence of thinning and thickening transformations applied to a gray scale image. As AP, the thickening profile is considered in the reversed order for which the high smoothed out image is placed as first and the original image as last. The input gray scale image, f, is also placed in the profile, since it can be considered as the level zero of both the thickening and thinning profiles. An EP can be mathematically given as in (2), where λ_i represents the number of maxima or minima preserved by an extinction filter and $\lambda_L > \lambda_{L-1} > ... > \lambda_1$.

2.4. Differences between Extinction Profiles

For APs, threshold values for the attribute being analyzed have been considered as a metric for the simplification of input images. This approach is sensitive to the image resolution, since, for instance if the attribute is the area of the structures, and we have a number of images that show the exact same scene, but one with the double of the resolution of the other, the thresholds to set the best attribute profile for these two images of the same scene would be different. On the other hand, the extinction profile, which is extrema oriented, would not suffer from this problem, since it is expected that both images have the same number of extrema, since they represent the exact same scene. It is possible to use attribute filters to set the number of extrema in an image, but due to extinction values ties, often it is not possible to set an exact number of extrema, making impossible to use attribute profiles using the number of extrema approach. Another difference of extinction profiles is that extinction filters preserve the height of the extrema, which contains relevant information for classification purposes. For a more in depth discussion see [6].

3. EXPERIMENTAL RESULTS

3.1. Data sets description and experimental setup

The first data set (Fig. 1) was captured over an urban area of Rome, Italy, acquired by the QuickBird satellite. It consists of a high-resolution (0.6m) panchromatic image. It has nine classes. The second data set (Fig. 3) is a high resolution panchromatic image of Reykjavik, Iceland, acquired by the Ikonos satellite. This data set is composed of six classes. It comprises residential, commercial and open areas.

A Random Forest classifier is used to classify the images. The Reykjavik data set comes with the train and test sets already split. In order to train the classifier, we performed a 5-fold cross-validation grid-search using the training samples and varying the number of estimators with the following values 300, 250, 200, 150, 90, 60 and the depth of the trees between 10, 15 and 20. We compute the Overall Accuracy (OA), the Average Accuracy (AA) and the Kappa Coefficient (K) to evaluate the classification results. The classification procedure was evaluated using the AP features and the EP features. The classification step for the Rome data set is repeated ten times, randomly selecting 10 % of the samples for training.

The area-open filter [10] is used to generate the APs using the thresholds $\{$ 25, 100, 500, 1000, 5000, 10000, 20000, 50000, 100000, 150000$\}$. These thresholds are the same used in [11]. In order to generate the EP, we used the area extinction filter. The values of n used to generate the profile are automatically given by the following equation:

$$\lfloor 2^j \rfloor \quad j = 0, 1, ..., s-1. \quad (3)$$

The total EP size is $2s + 1$, since the original image is also included in the profile. This equation was determined experimentally. We set $s = 10$, so that both AP and EP have the same length making it a fair comparison. The profiles were computed considering the 4-connected connectivity rule.

3.2. Classification Results

The classification results of the Rome data set are summarized in Table 1. The EP outperformed the AP by 0.74% in the OA, 0.64% in the AA and 0.9% in the Kappa coefficient.

$$EP(f) = \left\{ \underbrace{\phi^{\lambda_1}(f), \ldots, \phi^{\lambda_{L-1}}(f), \phi^{\lambda_L}(f), (f)}_{\text{thickening profile}}, f, \underbrace{\gamma^{\lambda_L}(f), \gamma^{\lambda_{L-1}}(f), \ldots, f, \gamma^{\lambda_1}(f)}_{\text{thinning profile}} \right\}, \tag{2}$$

The classification results of the Reykjavik data set are summarized in Table 1. The EP outperformed the AP by 1.97% in the OA, 3.44% in the AA and 2.35% in the Kappa coefficient.

As can be seen, the EP has improved the AP in terms of classification accuracies due to its capability to preserve more relevant regions suitable for classification. The second reason is that extinction filters preserve the height of the extrema which is useful for discriminating different classes of interest.

Table 1. Classification results of Reykjavik and Rome data sets by considering AP and EP with parameters defined in Section 3.1. Metrics AA and OA are reported in percentage. Kappa is a coefficient with changes in the range of 0 and 1. Best results for each data set is bold.

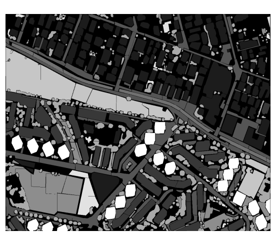
	Reykjavik		Rome	
Metric	**AP**	**EP**	**AP**	**EP**
OA(%)	81.04	**83.01**	84.99(0.05)	**85.73(0.05)**
AA(%)	75.37	**78.81**	86.24(0.16)	**86.88(0.08)**
Kappa	.7585	**.7820**	.8213(.0006)	**.8303(.0006)**

Fig. 3 illustrates a few features extracted by AP with the threshold values of 50000, 100000 and 150000 and EP with the number of extrema set to one, two and four. As can be seen, the EP can preserve more relevant regions for the classification while the AP discards those.

3.3. Influence of the size of the EP

Same as MP and AP, EP provides additional and very redundant features to the original data [1]. In addition, with limited number of training samples, the performance of the classification system will be downgraded beyond a few number of features due to the Hughes phenomena [12]. In order to handle such issues, the classifier should be capable of handling redundant features with limited number of training samples.

(a) Rome



(b) Reference map.

Fig. 1. (a) Rome satellite image and (b) its reference map.

(a) Reykjavik

(b) Reference map.

Fig. 2. (a) Reykjavik satellite image and (b) its reference map.

(a) AP

(b)

Fig. 3. (a) AP and (b) EP of the Reykjavik satellite image, for the filters with thresholds 50000, 100000, 150000, and set to keep 1, 2 and 4 maxima, respectively.

RF is one of those classifiers which can handle such issues to great extent [1] but its result can be still influenced by high redundant features. As can be seen in Fig. 4, the OA of the Reykjavik data set rises up to almost 85% by considering the profile size of 13 (including 13 thinning, 13 thickening and the original image) and then becomes almost constant. However, in this work, in order to have a fair comparison with AP, we only considered EP of size 10.

4. CONCLUSIONS

In this paper, a novel approach named extinction profiles has been proposed for the analysis of remote sensing data based on extinction filters. Then, the proposed approach was performed on two well-known panchromatic data sets; the Rome and the Reykjavik data sets and compared with one of the strongest approaches in the literature named at-

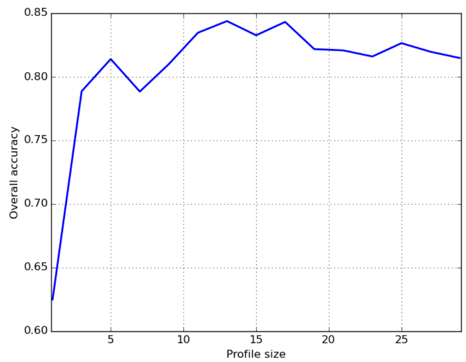


Fig. 4. Evolution of the OA of the Reykjavik data set, increasing the EP size.

tribute profiles.With respect to the experiments, the following promising points can be obtained: (1) extinction profiles can significantly outperform attribute profiles in terms of classification accuracies due to its capability to preserve more regions and correspondences detected by affine region detectors as well as preserving the height of the extrema, and (2) it works naturally with the number of extrema, which seems to provide better results in terms of classification accuracies and decreases the burden of setting threshold values.

As future work, we intend to investigate the use of EP using non-increasing features, such as standard deviation, using the methodology proposed in [13]. Also, we intend to investigate if the concatenation of AP and EP features can improve the classification results.

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