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RESEARCH ARTICLE

Quantitative descriptors for identifying plant species of urban landscape vegetation

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Abstract This paper discusses the ideas and methods of designing effective descriptors for identifying plant species of urban landscape vegetation. Fourteen of such descriptors induced from image spectrum, texture, and shape properties were designed. These descriptors were intended to meet such requirements as possessing a true physical or geometric implication relating to ecological significance, having a relatively steady segmentation threshold and being less sensitive to image types or environmental conditions during image acquisition. This study used decision trees to combine four selected descriptors for plant species identification, and the experiment was able to reach an error rate of 5.8% compared 25.9% by merely using the conventional pixel brightness values in plant species identification.

Keywords urban landscape vegetation, plant species, machine discerning, descriptor

1 Introduction

Plants of different species, even with the same canopy closure, often vary widely in their biomass, net productivity, and environmental effects. It is therefore necessary to distinguish between plant species when vegetation studies require precise quantification (Zhou and Sun, 1995; Zhou, 2001; Liu et al., 2008). Due to limited urban land resources and required artificial aesthetics, the urban landscape vegetation is often characterized with multiple plant species, uneven distribution, diverse spatial structure, and high-density vegetated parcels. Moreover, other types of landscape mixed with vegetation also exhibit high degrees of fragmentation and heterogeneity. All of the above issues make it a severe challenge for identifying plant species in remote sensing images, since the level of uncertainty in the detailed quantification of urban landscape vegetation seems to be beyond management (Baret et al., 2007; Buyantuyev and Wu, 2009).

To date, it seems that the reports on intelligent recognition of plant species are only seen for the secondary forest with a few plant species. The recognition is likely feasible for the species of secondary forest communities. Identifiable species are only up to 4 when using such data as radar, lidar, and multispectral scanner, etc. (e.g., Leckie et al., 2003; Santos et al., 2003). Using hyperspectral data, identifiable species can increase to 6 because the weenie differences in light absorption can differentiate different species (e.g,. Gong et al., 1998; Martin et al., 1998; Tan et al., 2005).

Therefore, the high heterogeneity in urban vegetation and other landscapes and the noises in remote sensing images would make the recognition of plant species often ill with no unique solution, if they would only rely on traditional spectral properties in the machine discerning. This paper introduces some quantitative descriptors as a feasible solution to this puzzle. The word “descriptors” in this paper means some mathematical expressions (Table 1). A descriptor expresses a certain image spectral, texture, or shape property in the level of a single pixel and/or its neighbors, a cell (seeing 3.2), or a plot (seeing scholium *c* below Table 1). The design of the descriptors of the present study allows the high-level knowledge of human experts fusing into descriptors and yielding some constraints over the basic operations. These constraints will likely help resolve the uncertainties in identifying plant species and speed up convergence processes of some learning machines.

2 Methods

The types of remote sensing images and the environmental conditions during image acquisition often vary significantly.

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As a result, the images in the same region, obtained at different time, will show greater differences in spectral properties. It is necessary to retrain a learning machine with corresponding training sets when using conventional spectral properties to identify plant species. Therefore, it is needed to design some so-called "generic" descriptors.

2.1 Basic principles of design

To be in broader sense, it is necessary that each descriptor proposed has to be linked to a specific nature of vegetation. These descriptors must also meet the following requirements:

1) possessing a true physical or geometric implication relating to ecological significance;

2) being of a relatively steady segmentation threshold and being less sensitive to the differences among image types or the environmental conditions under which the images are obtained.

2.2 Design of descriptor

Based on such conventional properties as NDVI, statistical indicators from a GLCM (gray-level co-occurrence matrix), shape coefficient, etc., we proposed 14 descriptors listed in Table 1. These descriptors, in accordance with the conventional classification of interpretation signs, can be divided into three types, namely, spectral, texture, and shape descriptors. Due to space limitations, Table 1 shows only the expressions of these descriptors. As the examples of definition and getparms, four descriptors of D_{SI}, D_d, R_a in Section 2.3, and C_d in Section 3.3 were discussed in detail.

2.3 Test the validity of descriptors

With some sampling data, the descriptors were tested one by one to ensure their validity on plant species identification (Table 1). The so-called validity means that the value of a descriptor can highlight some differences among plant species in order to generate a clear threshold for the segmentation.

Here, using D_{SI} (relative difference between saturation and brightness) as an example to validate its credit on identifying several species while comparing to other three single spectral components, i.e., H, S, and I. (Fig. 1). Plant species were obtained from 12 remote sensing images by two seasons, including cedar, metasequoia, and camphor, which are the most common species in Shanghai. It can be seen from Fig. 1 that metasequoia can be identified from others in a much better separation with the use of D_{SI} than that with one of the components of H, S, and I. In most of cases, there is an assured threshold of D_{SI}, which helps identify metasequoia from others. This result can demonstrate that a properly selected descriptor is able to minimize indetermination for threshold.

Table 1 New descriptors of identifying plant species with remotely sensed images

Sign	Name	Meaning[a)]	Validity[b)]
Spectrum descriptors			
A_R	Relatively red brightness	$A_R = (R\text{-}R_{avg})/R_{avg}$ (R: red brightness; R_{avg}: mean R; G, G_{avg} and B, B_{avg} by analogy)	★
A_G	Relatively green brightness	$A_G = (G\text{-}G_{avg})/G_{avg}$	★★
A_B	Relatively blue brightness	$A_B = (B\text{-}B_{avg})/B_{avg}$	★★
B_NDVI	Relative NDVI	$B\_NDVI = (B/IR - NDVI)/NDVI$	★★★
$NDUI$	Normalized difference umbra index	$NDUI = (\text{S-I})/(S+I)$ (S: mean saturation; I: mean brightness)	★★
D_{SI}	Relative difference between S and I	$D_{SI} = (S\text{-}I)/S$	★★★
C_d	Relative density of supplemental vegetation pixels	$C_d = D_{si}/A_i$ (D_{si}: supplemental vegetation pixels in cell i; A_i: vegetation pixels in cell i)	★★★
Texture descriptors			
T	Relative edge pixels	$T = S_{edge}/A_{NDVI}$ (S_{edge}: edge pixels; A_{NDVI}: the pixels tallying with $NDVI > 0.18$)	★★★
QF	Relative undulation	$QF = A_{holes}/A_{NDVI}$ (A_{holes}: small hole pixels on tree crowns)	★★
L_d	Density of bright details	$L_d = S_{light}/A_{NDVI}$ (S_{light}: pixels of bright details)	★★
D_d	Density of dark details	$D_d = S_{dark}/A_{NDVI}$ (S_{dark}: pixels of dark details)	★★★
Shape descriptors			
S_K	Density of skeleton	$S_K = L_S/D$ (L_S: length of plot[c)] skeleton; D: diameter of plot)	★★★
C_V	Undulating extention of edge	$C_V = A_{con}/A$ (A_{con}: pixels of crown convex, A: pixels of crown plot)	★★
R_a	Weighted mean crown diameter	R_a: the mean minor axis of plot outlines when each minor axis has its plot area as a weight.	★★★

a) Most of such values as area, mean, edge pixels, and so on, are calculated in a sliding window; b) ★ means valid occasionally, ★★ valid, ★★★ well valid; c) the word "plot" in this paper only means a region in which all pixels are similar in some image properties

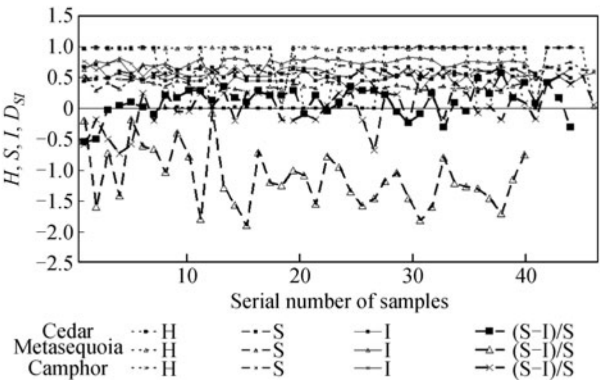


Fig. 1 Comparison of the capabilities of segmenting three plant species by H, S, I, and D_{SI}

Other example is given to the validity by using D_d (density of dark details), one of the texture descriptors. Small fluctuations on a crown surface will yield some small dark shadows or dark details whose density and mean length can be used to indicate the roughness of a crown surface. The gray-scale morphological filtering can serve as a feasible way to get D_d. Each continuous pixel set of dark details whose set size is smaller than a specified structural element can be extracted though a series of gray-scale morphological operations, namely, morphologically closeting an image and, then, opening the result. It is verified in several preliminary tests that D_d can indicate roughness of crown surface quite well. Figure 2 shows a clustering instance in which D_d serves as one of input components. The density of dark details is shown in Fig. 2(a), in which magnolia (with broad green leaves) and camphor (usually with several heads) have higher D_d values, while metasequoia (with a smooth appearance) has lower D_d value.

The last one is an experiment to test the validity of a shape descriptor. In the clustering pattern shown in Fig. 2, the R_a (weighted mean crown diameter) also serves as one of input components whose value is the mean minor axis of plot when each axis has its plot area as a weight. Figure 2(b) shows R_a in regular gray grades, and a lighter plot shows a higher R_a, namely, a larger crown diameter, and vice versa. Thus, the relative size of crowns can also serve as one of the key descriptors to identity plant species.

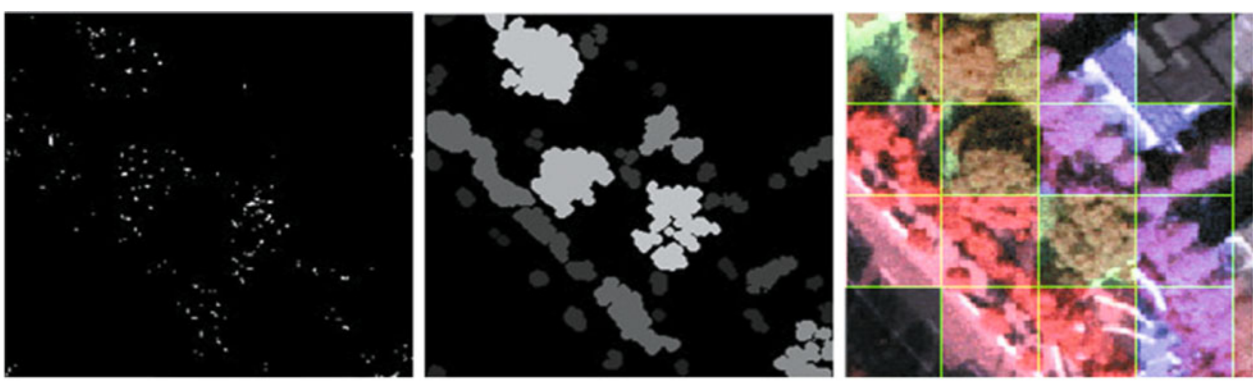
3 Discussion

3.1 Special roles of texture and shape descriptors

Both texture and shape descriptors play important roles in identifying plant species because they have a relatively steady segmentation threshold and are less sensitive to the differences between image types or to the environmental conditions under which the images are obtained.

Based on such traditional texture properties as GLCM statistics, wavelet analysis, etc., four new texture descriptors are designed to indicate the roughness on a crown surface (Table 1). One of the primary advantages of the texture descriptor comes from the matter that a descriptor value for a pixel is calculated with a certain neighboring of the pixel rather than with a plot the pixel belongs to. Usually, a plot is a result of previously defined segmentation. A remarkable shortcoming is that it is difficult to obtain continuous homogeneous segmentation results because the value distribution of a texture descriptor is often discrete. Our solution to this problem is in the use of a so-called "cell" (see Section 3.2).

Shapes not only with bright plot but also with dark one on a crown image can be indicated by some shape descriptors on the basis of a region or a boundary of the plot. Using such conventional shape properties as a plot area, the shape coefficient as well, three new shape descriptors are designed to indicate the complexity of a crown outline and its relative size (Table 1). The value of a shape descriptor is an overall quantity of a plot; so, these descriptors can perform well against the image noises. However, there is also an obvious shortcoming in the use of shape descriptors because these descriptors have excessive reliance on the previous segmentation. If the



(a) (b) (c)

Fig. 2 An instance of clustering with a combination of four descriptors. (a) Distribution of D_d; (b) grade chart of R_a; (c) output of clustering boundaries of the plots obtained from the segmentation are not accurate enough to show those crowns on an image, it is hard to take the shape descriptors into use. Our solution to this problem is to take a multidescriptor combination, including the use of those nonshape and without-presegmentation descriptors, thus reducing overreliance on the plots.

3.2 Significance of cell use

Vegetation in urban landscape often appears scattering or line-ranged layout. Large planted areas with only a single species can be seen occasionally. Usually, it is difficult to obtain a desirable result while segmenting or clustering plant species from a whole image. In addition, other cases also often make the results invalid, such as discrete texture properties and "round tendency" in a fuzzy clustering as well. A solution is to take the use of grid-based method with which image space is separated into a finite number of cells and then to have cell segmentation or cell clustering.

With cell operations, the gray undulation and random noise of texture properties can be smoothened when taking the weight-mean of a texture descriptor in a cell as the cell value. Furthermore, it will make those formerly difficult operations (i.e., segmentation, clustering, etc.) more feasible. Most tests in this paper have used cells. For example, using combined multidescriptors can work out the result of cell clustering (Fig. 2) and using the decision tree to obtain cell multisegmentation (seeing 3.4).

The precision of a cell operation depends largely on cell size. Here, the cell size is specified as $25\,\mathrm{m} \times 25\,\mathrm{m}$, considering that those trees have larger crown sizes. To facilitate the extraction of shape properties, it is necessary to detect a full crown. According to interpretation and statistics on remote sensing images, the greatest crown diameter in Shanghai is generally between 20 m and 25 m.

3.3 Use of additional constraints

Several new descriptors were derived from conventional properties but with some additional constraints. When extracting vegetation with *NDVI* for the purpose of obtaining a supplemental set of vegetation pixels, let us take *SAVI* as an example, as shown below.

NDVI is one of the early generic properties for extracting vegetation. Using the formula $NDVI = (IR - R)/(IR + R)$ (*IR* means infrared and *R* red brightness), the condition $NDVI > 0.18$ is valid for extracting most plant species of urban landscape vegetation. However, those species with a smaller difference between *IR* and *R* appear to have no saturated red in a color infrared image (seeing some trees in Fig. 3(a) pointed by blue arrows). To extract these species, reducing the *NDVI* threshold is needed. For example, *NDVI* threshold should be reduced by up to 39% for the purpose of extracting metasequoia. As a result of reduced *NDVI* threshold, it is possible to have other nonvegetation surface types to be extracted, such as the surface of granite in shadow color.

It is verified that this problem can be solved by additional constrains. For instance, using the following formula can effectively extract supplemental vegetation pixels in the low red saturation level, like that of metasequoia on a color infrared image, and can restrain the disturbers from other surface types.

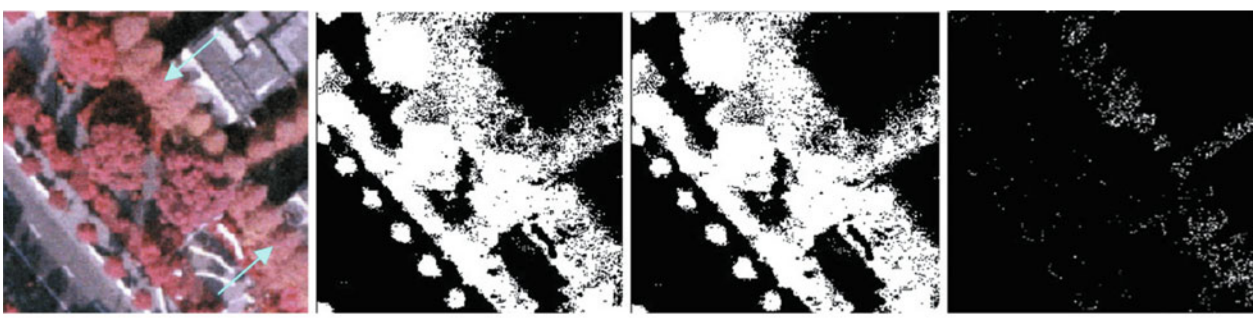
$$S = \{S | S \subseteq IM, S = (NDVI > 0.11) \cap (SAVI > 0.18)\}, \tag{1}$$

where *S* is the set of pixels belonging to metasequoia; *IM* is the set of entire image pixels; *SAVI* means soil-adjusted vegetation index, and $SAVI = \left((IR - R)/(IR + R + 0.5)\right) \times 1.5$ (Huete, 1988; Gao et al., 2000).

Therefore, we can get D_S as the supplemental pixel set in the low red saturation level as follows:

$$D_s = \{D_s | (D_s \subset S) \cap (D_s \square NDVI > 0.18)\}, \tag{2}$$

Figure 3(c)) shows the situation by adding set *S* to the original set of vegetation pixels in Fig. 3(b). Figure 3(d) shows the D_S set calculated with Eq. (2). It can be seen that those poorly extracted metasequoia pixels can be supplemented quite well with D_S. It is more than that with the supplement that the full range of vegetation cover can be



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

Fig. 3 An instance of extracting supplemental vegetation pixels in the low red saturation. (a) Original image; (b) $N = NDVI > 0.18$; (c) $N \cup S$; (d) D_S

well extracted. More importantly, the relative density of D_S, namely, C_d (Table 1) also can serve as an important descriptor to extract these species in the low red saturation level like metasequoia.

3.4 Accuracy examination

When using a single descriptor, only a few individual species can be identified under specific conditions. The classification in multiproperty space with the combination of multidescriptors will help increase the number of identifiable species and thus will improve the accuracy of classification. On the basis of the evaluation of descriptors and understanding the properties of plant species, the input vectors, each corresponding to a descriptor can be decided for a learning machine.

To make an accurate examination of identifying plant species with descriptors, we use the scene of colored infrared aerial photograph (seeing Fig. 3(a)) and the four-descriptor combination as the input property vector. These descriptors are $NDVI$, D_d, R_a, and C_d, which represent spectrum, texture, shape properties, and pixel supplement, respectively. A conventional combination of spectrographic brightness is also taken as a reference. The learning machine used is a decision tree.

Figures 4(b) and (c) are the two identified results with the combination of $NDVI$, D_d, R_a, C_d, and the combination of spectrographic brightness. The charts were formed by incising the top left corner of the two outputs because there are so many cells in the outputs that the marks of plant species cannot be shown clearly for reading. In this case, data are spaced into certain sizes of cells (cell No = 342), of which the cells with $\geqslant$10% vegetation cover are 139. Table 2 shows a comparison of identification accuracy with these two combinations. Number of incorrectly divided cells is counted by visual interpretation. The error rate here means that the ratio of the number of incorrectly divided cells to the number of cells with $\geqslant$10% vegetation cover. A complex species cell means such a single cell that it contains two or more species, but it is irrelevant to prioritization. The number of complex species cells is 11 (possessing 7.9%).

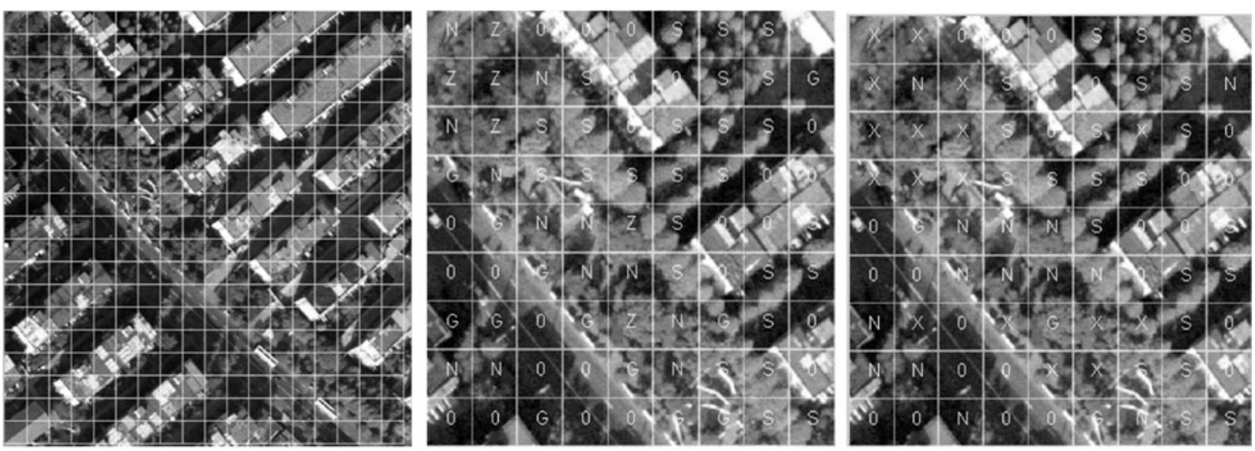
The error rate of identification with the combination of $NDVI$, D_d, R_a, and C_d is obviously lower than that with the combination of spectrographic brightness, and the difference between them is 77% (Table 2). Thus, in the multiproperty space in accordance with the combination of $NDVI$, D_d, R_a, and C_d, the uncertainty of identification is greatly reduced. Therefore, incorporating human expert's knowledge into these descriptors will form some constraints over the basic operations. This can also enrich the organized data levels, namely, to have a new level of spatial objects above the conventional level of a single pixel.

4 Conclusions

This paper proposes 14 new descriptors, which can help indicate spectrum, texture, and shape properties, respectively.

Table 2 Comparison of identification accuracy

Input vector	With the combination of $NDVI$, D_d, R_a, and C_d	With the combination of spectrographic brightness
Number of incorrectly identified cells	8	36
Error rate	5.8%	25.9%



(a) (b) (c)

Fig. 4 Comparison of identification accuracy with two different property combinations. (a) Original image; (b) combination of $NDVI$, D_d, R_a, and C_d; (c) combination of spectrographic brightness. Z—camphor; S—metasequoia; G—magnolia; X—cedar; N—privet; 0—cell having < 10% vegetation cover

Through statistical analyses, together with the tests of image classification and/or clustering, it is demonstrated that these descriptors can perform better than that with conventional properties in identifying plant species of urban landscape vegetation. In addition, the algorithm of extracting supplemental vegetation pixels can help obtain the full range of vegetation cover. Also, the relative density of supplemental vegetation pixels can serve as an important descriptor to extract those species in the low red saturation. With the cells, the random noise of the texture descriptors can be smoothened, and some algorithms are likely to be simplified. It is verified by an accurate examination that the error rate of identification with the combination of *NDVI*, D_d, R_a, and C_d is 77% lower than that of the combination of spectrographic brightness.

So far, using verified descriptors of the present study can identify 12 plant species of urban landscape vegetable, further improvements can be expected along with in-depth studies on suitable descriptors, and more robust learning machines need to be verified. Our ultimate goal is to make up to 30 backbone plant species identifiable, which can likely account for $>90\%$ of the total individual plant in a large-scale city.

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