FINDING A GOOD SEGMENTATION STRATEGY FOR TREE CROWN TRANSPARENCY ESTIMATION

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ABSTRACT

Image segmentation is a general term for delineating image areas into informational categories. A wide variety of general techniques exist depending on application and the image data specifications. Specialized algorithms, utilizing components of several techniques, usually are needed to meet the rigors for a specific application. This paper considers automated color image segmentation of foliage representing pixels for the purpose of crown transparency estimation. Varying image characteristics caused by differing levels of foliation and fluctuating lighting conditions present a unique challenge for consistent segmentation in order to reliably measure tree crown transparency. Small leaves surrounded by bright sky, small openings among dense canopy, and mixed pixels all present difficulties for segmentation. This study found the green band to be most helpful for preserving pixels representing reflectent leaves surrounded by pixels representing sky. Texture was useful for preserving other small portions of tree canopy in sky dominated regions. Scale considerations and automated methods are also discussed. The initial stages of a segmentation approach are presented, but further work is required for segmenting pixels in the fuzzy regions.

INTRODUCTION

Image segmentation is a general term for delineating image areas into informational categories. Techniques can vary widely depending on the application and the image data specifications. For the purposes of this paper the term image refers to a digital, spatial data structure in two dimensions (x,y), consisting of equal-sized discrete units (pixels), which represent some measured quantity or digital number(DN). For photographic images, this measured quantity is light. Often a set of congruent images are collected and analyzed together. For instance, most consumer digital cameras capture light in three separate spectral ranges (red-green-blue, RGB). In this paper the term band will be used to denote one of a set of congruent images.

Specific methods of image segmentation have been categorized differently using a variety of terminology (Sahoo et al., 1988, Jähne, 1997). In general, DN, alone or in combination with derived features (i.e., texture, adjacency, etc.), are separated into one or more groups based on some decision rule. Thresholding and classification are two forms of image segmentation. Sahoo et al. (1988) and Glasbey (1993) present surveys of thresholding techniques. Here thresholding is presented as the categorization of pixels of a single band into two levels (binarization), though multilevel thresholding is also discussed. Classification typically refers to multiple bands and multiple information classes. The terms thresholding and classification are often used loosely in the literature and likely originated in different disciplines, but both describe image segmentation.

As there are myriad methods of performing segmentation, the decision of which to use falls on application developers. The choices of features, domains, and decision rules all factor in the formulation of the overall strategy. Martí et al. (2001) state that no one color space or segmentation method has been shown to be superior for treating images of outdoor scenes. The algorithms presented in the literature are often intended to be generalized, but frequently the most successful vision systems begin with a top-down model driven approach (Hild et al., 1992). The application discussed in this paper concerns transparency measurement of tree crowns. Transparency is defined as the amount of skylight visible through the live, normally foliated portion of the crown (USDA Forest Service, 2002). The difficulties inherent in evaluating transparency are discussed in numerous papers (Ferretti, 1997, Innes, 1988, Kramer, 1986) and will not be a consideration of this paper. This study focuses on images of trees captured from a single ground-based viewpoint under different natural light conditions. Images were captured ensuring a significant portion of the frame contained sky background.

This paper will briefly examine some of the methods commonly used for color image segmentation in general. Then methods targeted toward foliage evaluation applications will be covered. The usefulness of various features and methods for this application will be covered. A discussion of a proposed framework will be presented in addition to conclusions and suggestions of future work.

CONSIDERATION OF IMAGE SEGMENTATION METHODS AVAILABLE

The simple definition of image segmentation is partitioning an image into homogeneous regions. A formal definition given by Pal and Pal (1993) is as follows: if F is the set of all pixels and $P(\ )$ is a homogeneity predicate defined on groups of connected pixels, then segmentation is a partitioning of the set F into a set of connected subsets ($S1, S2, \ldots, Sn$) such that

$$\bigcup_{i=1}^{n} S_i = F \text{ with } S_i \cap S_j = \Phi \ \ (i \neq j).$$

The uniformity predicate $P(S_i)$ = true for all regions S_i, and $P(S_i \cup S_j)$ = false, when $i \neq j$ and S_i and S_j are adjacent. But while there is a formal definition, the evaluation of the quality of segmentation methods is still very vague as the homogeneity predicate is often a proxy intended to represent real-world objects. For this application, the desire is to partition color image pixels into meaningful informational categories. This can often present problems where different informational categories may overlap in one or more variables of the homogeneity predicate (Saha and Udupa, 2001, Karmakar and Dooley, 2002).

Many thresholding methods (Sahoo et al., 1988, Sankur and Sezgin, In Press) are available for separating values in one band of data. This is expanded to clustering methods in color image segmentation where multiple bands are considered. The general categories of classification techniques presented by Cheng et al. (2001) and Lucchese and Mitra (1999) are: 1) histogram thresholding, 2) feature space clustering, 3) region-based approaches, 4) edge detection approaches, 5) fuzzy approaches, and 6) neural network approaches. Spectral characteristics vary widely due to outdoor lighting conditions, leaf shapes, and shading factors. This precludes the practical use of feature space clustering and neural network approaches, so these will not be considered further for this application. The remaining techniques all have strengths that have potential to aid in a successful method.

The list of possible methods to perform segmentation each have their trade-offs for speed and accuracy, simplicity and complexity, and application to specific datasets. Image understanding concepts can be used to drive a model that can direct a segmentation strategy. Features can be identified and known difficulties addressed in order to use the best method for certain classes within the image. Image analysis is used in conjunction with a knowledge base to determine the best segmentation strategy and to set model parameters.

SPECIFIC METHODS INVOLVING OUTDOOR AND FOLIAGE APPLICATIONS

As a part of a larger objective of tree crown assessment, the goal of this particular project calls for the segmentation of foliage pixels. At this time, no effort is being made to separate other canopy structures (e.g., twigs, branches, vines, animal nests, etc.), though these are excluded by definition and shown to affect transparency estimates (Lee et al., In Press). Global binary thresholding has been used in other tree crown studies (Mizoue and

Inoue, 2001), however, a locally adaptive thresholding procedure appears more appropriate for consistent evaluation over the entire image space (Tian and Slaughter, 1998). For crown assessment often the interesting details are changes in local intensity which may not be significant in the overall range of the image (Rich, 1990). High variability of image features and bad local feature separation are listed by Hild & Shirai (1993) as difficulties in ground-level natural scene interpretation. Figure 1 shows how the Otsu (1979) threshold can miss some locally interesting information.

Figure 1. Otsu's thresholding method (center) applied to the blue band of the original RGB color image (left) shows that valuable details are lost. The rightmost frame demonstrates that adaptive methods are needed to as pixels that are globally darker (2) should be classified as sky, while those that are globally lighter (1) should be classified as canopy.

There are many different foreground objects which may occlude the canopy of interest, as well as a large array of background objects with differing spectral properties. In order to simplify this study, the main interest will be to segment pixels representing tree canopy from pixels representing sky. Mizoue and Inoue (2001) show that a variance-based (Otsu, 1979) method is superior to classification error (Kittler and Illingworth, 1986) or entropy-based (Kapur et al., 1985) methods for a single, global threshold. The authors mention that reflective foliage presents misclassifications on some images. In these studies the blue band was used as it contains the greatest contrast. So, although a grayscale technique is employed, color information is provided by the sensor.

SELECTING USEFUL FEATURES

Defining useful features is the first step in formulating a limited knowledge base that will be used to guide the process. Figure 2 represents the typical image collected for this application with tree and sky being the two main groups of interest. Sky attributes include bright, non-green, low texture, and large regions. Tree attributes include dark, green, and high texture. This indicates that color, intensity, edges, and regions will all contribute to accurate segmentation. These generalities are not mutually exclusive giving rise to the problem of this study of determining how best to segment the image pixels into these categories.

Intensity

Intensity refers to the actual amount of light recorded by the digital sensor and provides the contrast necessary in most instances in order to detect that information is present. Due to the fact that intensity is the primary unit recorded, it is the logical first choice to consider for segmentation. Intensity is normally the sole value used with global thresholding methods. This is quite appropriate for many applications such as document scanning where the data collected is targeted toward intensity.

In an outdoor situation intensity can vary widely. The orientation of the sun with respect to objects being imaged and atmospheric characteristics have affects on intensity before it reaches the sensor. For the purposes of this study the urban tree data are collected while the sun is greater than thirty degrees above the horizon and in all but the very most overcast conditions. The only sun position disallowed is directly behind the object of interest as it can create such extreme blooming as to interfere with accurate measurements.

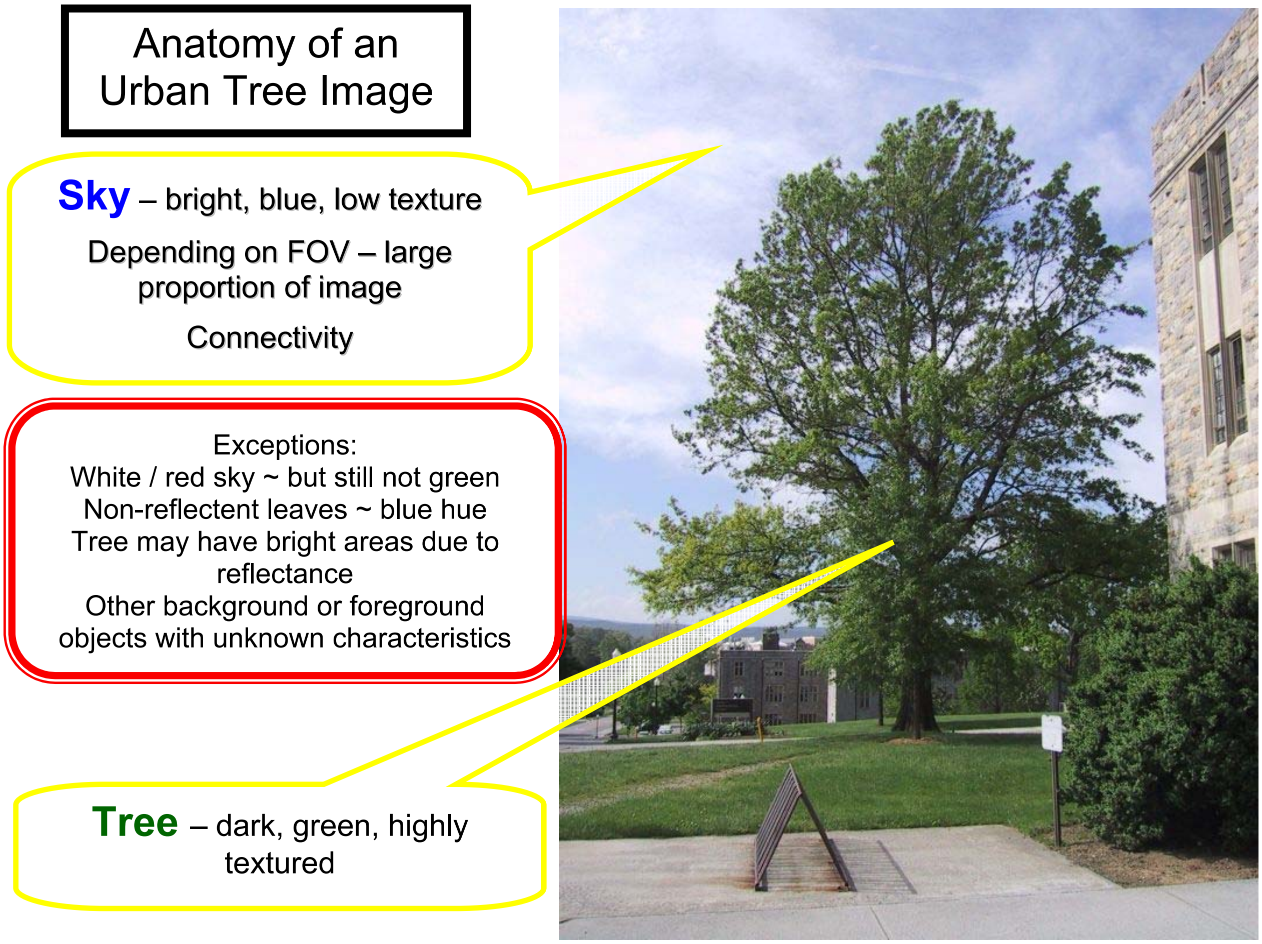

Figure 2. This typical urban tree image demonstrates the characteristics the sky and tree components.

Most imaging systems, including the human eye, are designed to adjust to certain ranges within this variation. There are upper and lower limits for known sensors. Aperture and exposure are adjusted in order to obtain the maximum information within the range of the sensor. For this study, automatic settings for these parameters controlled by the digital camera were accepted. Recommendations for future work would be to increase the exposure a stop above auto for conditions where the sky is very bright and there is no reflectance from the foliage, and reduce exposure a stop below auto for conditions where there is strong reflectance from the foliage.

Figure 3 shows the intensity histogram for the frontlit canopy image in the same figure. No strong peaks are present to indicate a good separation based on intensity alone. It may also be apparent that the intensity of some reflective foliage areas would be greater than that of some foliage areas among a large amount of ambient light. Some of this problem may be solved at the collection phase by prohibiting image capture with front or side lighting, but this restriction would tremendously hamper practical field collection.

The difficulty with segmentation using intensity is caused by reflectance from the front side leaf surfaces. Color and adjacency can be used to assist in the proper classification. Mixed pixels at the edges between canopy and sky classes also add ambiguity. These issues will now be discussed in turn.

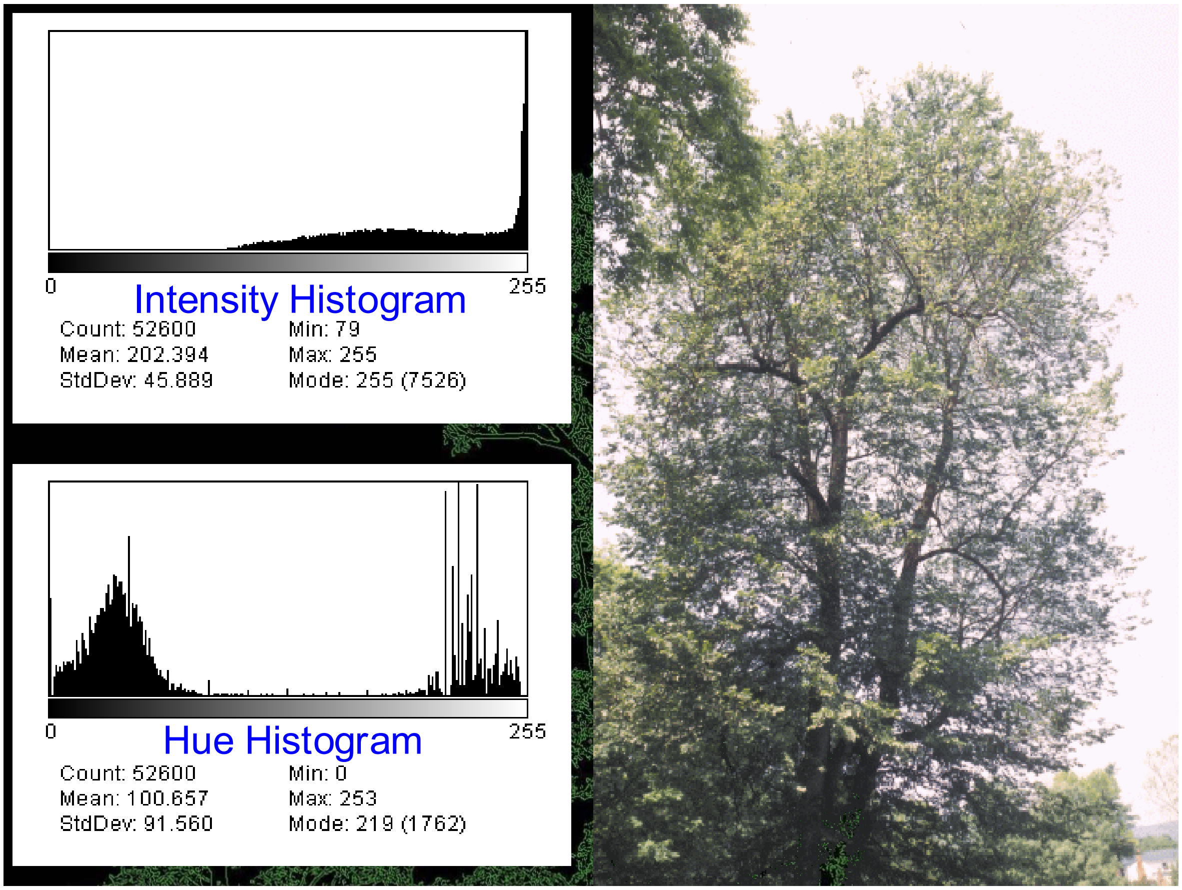

Figure 3. Hue and intensity histograms for color image displayed at right.

Color

Much work has been done to determine the best color space to use for various classification schemes (Cheng et al. 2001, Martí et al. 2001, Philipp and Rath 2002). An example of the components of the HSI transform can be seen in Figure 4. Prior to the concern of which color or color space transformation is best for discrimination after the image is captured, it is realized that lens, filter, and camera processing parameters should all be considered in optimizing discrimination at the image acquisition phase. However, this study is constrained to the 24-bit RGB (red, green, blue) output image from a consumer level digital camera.

Haering and da Vitoria Lobo (1999) indicate that over the course of a year deciduous tree leaves may take on all colors except blue. Additionally shaded objects, including leaves, tend to take on the ambient blue hue from the sky radiance. As such, color itself can be of little use in discriminating potential leaf pixels. However, for the purposes of tree health, data collection is restricted to a short time representing full leafout. Leaves should then always be green excepting a few unique species or definitely unhealthy trees.

Color information is very useful for this application as the sky and vegetation should have distinct chromatic differences. However, whether frontlit or backlit, achromatic areas are typically present in all tree crown images. This presents a problem as hue is known to be unstable in areas of low saturation (Cheng et al. 2001, Tico et al., 1999). For the frontlit condition this is often due to internal shading among the crown components. As previously mentioned, the blue band shows the greatest contrast in tree crown images. This is apparent when viewing the separated bands in Figure 5. This occurs as atmospheric properties of the sky cause it to be highly reflective in the blue band while the foliage is highly absorbent in the blue band. This makes the blue band very useful for reducing the amount of reflective foliage that could be confused with sky when using intensity thresholding. It is also apparent in the frames of Figure 5 that some foliage areas that are apparent in the green band are not in the blue band. This is because objects, including leaves, that do not receive sufficient amounts of incident radiation tend to take on the ambient blue hue from the sky radiance in outdoor images (Haering and da Vitoria Lobo 1999). It is for this reason that one color alone is insufficient for optimal thresholding and one main reason why color imagery is used for this application (Figure 6).

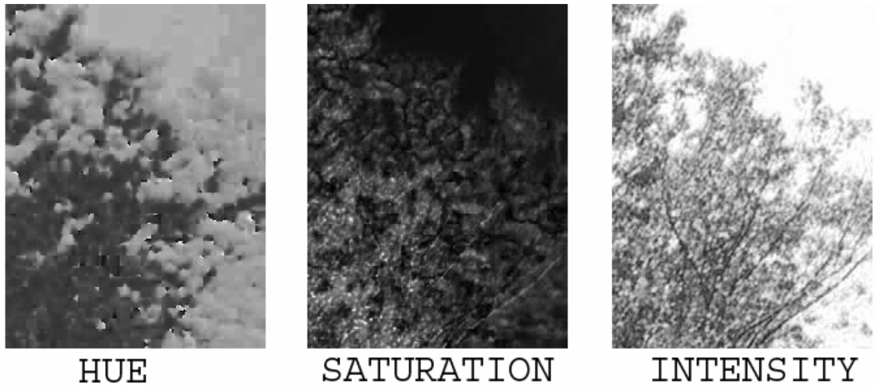

Figure 4. Display of the hue, saturation, and intensity layers of the HSI transform.

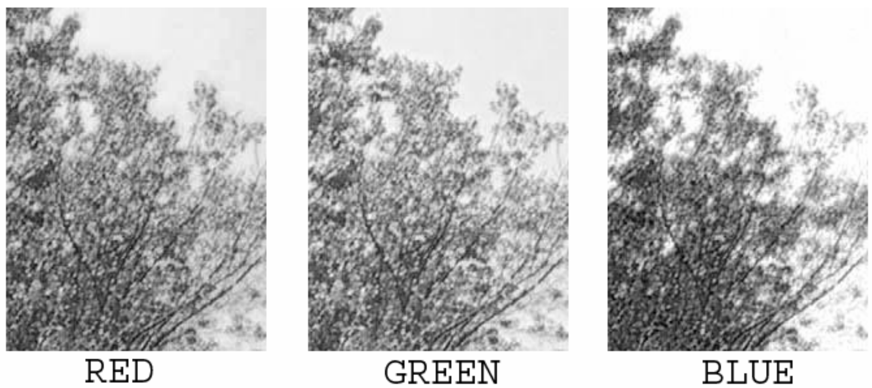

Figure 5. Display of separate red, green, and blue bands of a typical 24bit RGB image.

Figure 6. Demonstration of how the addition of color information aids in easier discrimination of reflective foliage and sky background.

An issue that should be recognized when using digital imaging is the effect of varying image manipulations that occur. Modern consumer digital cameras have many features which modify captured images prior to writing to memory. These may include white-balance adjustment, edge sharpening, color enhancement, and perhaps many others. These are then often followed by some image compression for efficient storage. However, lossless compression techniques such as the popular JPEG compression scheme can create serious effects. This is particularly apparent in the hue component (Figure 4) as one of the steps in color image compression is color quantization which reduces the number of hue values reported. It is beyond the scope of this paper to examine all of these possible features as they are different for each camera manufacturer and model. Mention is made only to inform that these manipulations take place and the effects are most obvious among the color component.

Texture, Edges, and Regions

Texture, edges, and regions are all similar in that they denote an amount of change of one or more features (intensity, hue, etc.) over a distance or area. Texture is a perceptual entity that is characterized by changes in the magnitude, direction, and periodicity. Regions are representations of similarity in space, while edges are measures of dissimilarity. Texture features were shown to outperform color and intensity for locating deciduous trees in a set of digital images (Haering and da Vitoria Lobo 1999). And it is widely known that texture is a prominent characteristic in natural scenes.

It is intuitive that texture measures of the sky and of the foliated crown would be highly separable. This can easily be seen in Figure 7 where the gradient measures within the crown area and between the crown and sky are much greater than the gradient of the sky area.

Figure 7. Edge detection showing high gradient values within the tree crown region and relatively low values among the sky region.

Scale – Resolution

Scale and spatial resolution are primary considerations in any remote sensing application. Analysis of these factors must be performed before the study is undertaken and data collected. Scale and resolution enter in to this study as decisions are made in regards to the collection, camera, and analysis parameters. The field collection protocol is predefined as the data are collected from the ground at the tree height distance from the base. The camera constraints are primarily limited by budget in regards to lens magnification and imaging sensor array dimensions. Due to the fact that these other factors are set, the scale of the analysis must be adjusted. Jennings et al. (1999) point out that a decision is required a priori to define the minimum canopy opening that will be considered. This too would apply to the minimum leaf size or foliated area represented. Ideally, the analysis should dictate the scale of data collected and that will be the discussion of another study.

Scale is integral to crown transparency work as trees at different levels of foliation will have canopy openings of varying sizes and number. The area/edge ratio or DSO (Mizoue 2001) is largely affected by spatial resolution. This is particularly true as branches and even individual leaves are separated by varying distances and have nearly random orientations in space. Sampling should be done at the Nyquist frequency, meaning that the optimal resolution should be one-half the width of the primary unit. In the case of crown sampling for foliage estimation it would appear that a single leaf would be the smallest sample unit. However as leaves have complex shapes and orientations cannot be controlled, the thickness of a leaf or needle is usually less than a millimeter. Sampling at this rate would be prohibitive. Further study should be given to finding an acceptable scale for this application.

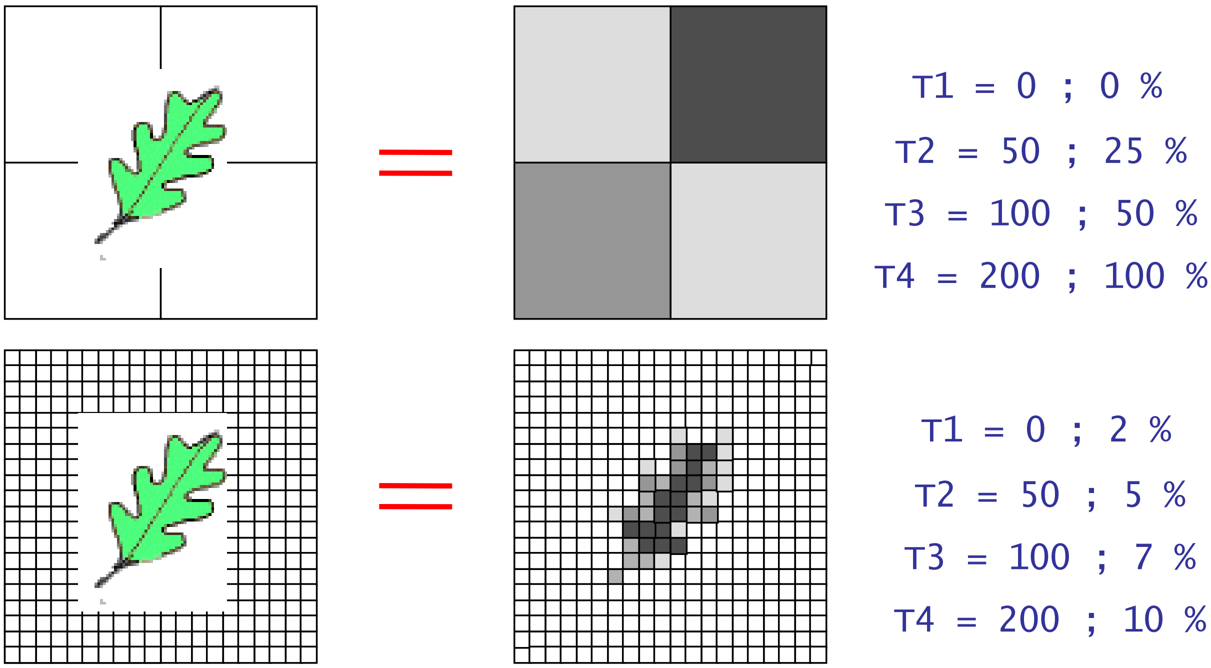

Figure 8. Depiction of a leaf sampled at two different spatial resolutions over a range of spectral thresholds (T1, T2, T3, and T4) with the percentage of total object space area represented.

DISCUSSION AND CONCLUSIONS

Certain problems exist in applying image segmentation for tree crown transparency estimation from ground-based images. Many of these have already been mentioned in general terms. Specifically, the need is to find an automated method that will have the ability to adapt to various outdoor imaging problems and provide consistent transparency estimates regardless of the level of foliation.

Automated Methods

The effort to use digital images for tree crown transparency evaluation will only be worthwhile if it is cost effective. In order for the image processing to be cost effective it must be an automated process requiring minimal human guidance. Automation is a challenging prospect in that certain parameters must be chosen for almost every image processing operation. In image classification, which is related to segmentation, much effort is being placed into finding the best unsupervised methods of classifying pixels into informational classes. K-means and ISODATA methods are the most frequently used and are data-driven, iterative methods. However, they are not adaptive in their primary forms.

The K-means (or C-means) method has been extended to fuzzy sets (Cheng et al. 2000, Lucchese and Mitra, 1999) and these fuzzy methods have been combined with knowledge-based (Nanayakkara and Samarabandu, 2003) and spatial constraints (Liew and Yan, 2001). A combination of these methods appears necessary for the proper segmentation of the most difficult pixels.

Sparse leaves in open sky and small sky patches among a dense crown

As this system must cover the range of foliage conditions, it has to be able to detect only a few small leaves in an image dominated by open sky. Direct reflectance and resolution limitations can be problems when this situation occurs. As there are fewer leaves in the overall canopy, the probability for specular reflectance is much greater. Even a high level of reflectance decreases the separability of leaves and sky based on intensity. In this case color is essential for segmentation. When these individual leaves are small or at acute angles to the camera viewpoint, spatial resolution can be a limiting factor. In this situation, gradient is often the best feature for segmentation.

Small sky openings among a dense canopy can suffer from many similar problems to the inverse problem just mentioned, but often to a lesser extent and usually with less significant meaning to the final diagnosis. In this situation the transparency value for the crown is typically very small. Unless there are large numbers of these small openings, they will do little to influence the level of transparency. Conversely, in the case of many small leaves among a largely defoliated crown, the lessened ability to detect leaves coupled with the potential for major deviation in crown boundary fluctuation may have much larger consequences. Small openings within a fully foliated crown are unlikely to change the boundary being considered.

Rarely, a situation may occur where there may be a highly reflective leaf adjacent to a sky opening (Figure 6) and this may need to be rectified in a verification step. The primary issue with segmenting a small sky opening from surrounding crown pixels has to do with mixed pixels and edge determination. This must also be coupled with some minimum size limit.

Mixed Pixels

Mixed pixels occur on spatial boundaries between object types and are inevitable with any non-continuous sampling. Increasing resolution may decrease the severity of the area effect but will increase the number of mixed pixels. Usually mixed pixels are pushed into the most probabilistic class with the assumption that the errors will offset. This may only be true with many assumptions. Bayesian methods are hard classifications with limited flexibility and allow no overlap. For this study we will use a fuzzy classification and assign mixed pixels with a rule-based decision scheme as context may take precedence over feature value groupings. This aspect is still in development.

Order of Operations

The order of operations can provide sufficient accuracy, while reducing the computational burden. One way that this is done is by using basic methods to classify and mask out easily segmented pixels or regions. One approach would be to iteratively segment by dividing based on one feature, then using another feature under that mask to refine the classification. This is similar to fuzzy c-means methods, however multiple features are considered.

The current method is as follows (Figure 9). Following the indications from the work of Mizoue and Inoue (2001) an effort was made to use the blue hue to separate the sky from the crown. The HSI transform was used to determine the hue as it is invariant to lighting (given certain assumptions). A determination had to be made as to what defined "blue". Often the sky is achromatic and the sky pixels are dominated by a red or a neutral white hue. It was determined that "not green" was a better designation than "blue" as the blue hue can be dominant among shaded leaves and in no case was green dominant among sky pixels. Finally, a G>B (green greater than blue) mask was applied rather than hue for simplicity and as this result could be used within the knowledge base. This mask will contain all green dominated pixels within an image including other vegetation and foreground or background objects. Spatial methods and texture measures will have to be applied to excise these extraneous regions.

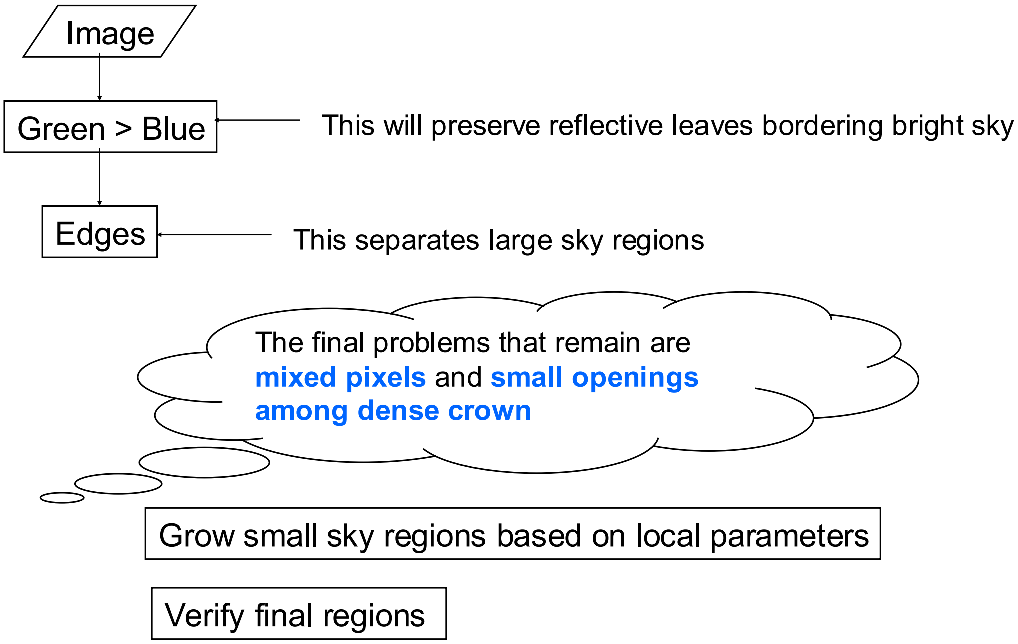

Figure 9. Partial procedure for image segmentation of tree canopy and sky pixels

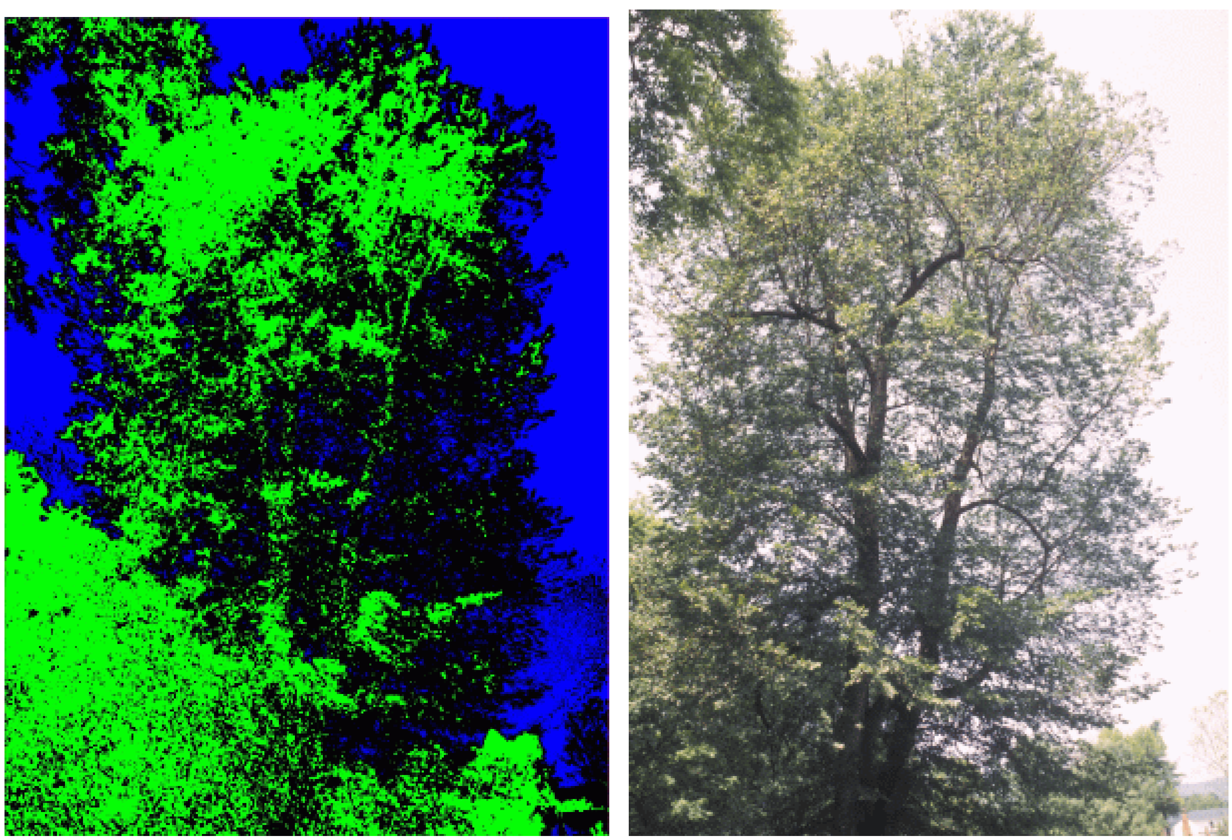

Figure 10. Initial confident classification of vegetation and sky. G>B (green greater than blue) filter (pixels shown in green) is used to preserve reflectent leaves. Low-textured, bright, non-green regions are found to determine more specific intensity and hue sky parameters from the data. These parameters are used to classify the confident sky

pixels (blue in figure). The remaining pixels (black) are would be the fuzzy intersection between sky and crown classes.

Next a gradient operator is applied (Figure 7) to examine texture over the scene. Dilation is applied to the high gradient pixels and regions are computed. Large regions are then examined by their location and spectral properties. These large regions which are relatively bright, low-textured, and located in certain relative positions within the image are considered representative of sky. Spectral parameters of sky can then be determined in a data-driven manner and added to the knowledge base for that particular image. The results of this stage of classification can be seen in Figure 10. The green dominant pixels are portrayed in green and sky pixels determined by values obtained with the region method are shown in blue. The black region contains the unclassified pixels to be given further scrutiny. Low intensity values will likely be easy to extract from this group. The remaining pixels would be sparse leaves surrounded by sky, small sky openings surrounded by crown, and mixed pixels.

The remaining pixels represent trouble areas and areas where feature spaces overlap. For this reason more complex classification methods are required taking context into account. This portion of the research is still ongoing, but a proposed approach follows. As the location of the large sky regions are known, a localized region growing process may be used to determine the final classification of these pixels. Small sky openings within the crown dominated area will be detected by examining iteratively decreasing intensity values, beginning with intensity values determined by the sky region analysis previously performed. Directional step edges may be applied to determine the actual boundaries of these openings. A verification step will be run on these openings to ensure that the minimum size criterion is met. In all cases, intelligent classification methods are needed that are locally conditioned. Higher resolution imagery may be used to examine the effectiveness of these segmentation methods.

This study has reinforced the fact that feature-based segmentation techniques excluding the knowledge of context and inter-pixel relationships can produce unsatisfactory results due to overlapping pixel values between classes (Saha and Udupa, 2001, Karmakar and Dooley, 2002). Useful feature spaces for this application have also been identified. Although the blue band exhibits the most contrast within a single band, the green band is more exclusive among classes. Shaded canopy components can often assume a blue hue, while green hue was never found to be dominant for sky pixels. Texture in combination with region growing was found to be useful for finding sky regions. Hue and intensity parameters for sky pixels can be determined from these regions providing a flexible automated method. Problem areas for classification were identified and some solutions proposed. Further work is required to classify these fuzzy pixels within a contextual framework. It was also recognized that scale is an important factor and should be considered at the data collection, camera, and analysis phases. The resolution of these remaining issues should further the progression toward an automated and reliable method for foliage transparency estimation.

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