Enhanced Gap Fraction Extraction from Hemispherical Photography

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Abstract— **Canopy structure can be estimated using gap fraction (GF) data, which can be directly measured with hemispherical photography. However, GF data accuracy is affected by sunlit canopy, multiple scattering, vignetting, blooming, and chromatic aberration. Here, we present an algorithm to classify hemispherical photography, whose aim is to reduce errors in the extraction of GF data. The algorithm, which was implemented in free software, uses color transformations, fuzzy logic, and object-based image analysis. The results suggest that color and texture, rather than only brightness, can be used to extract GF data.**

Index Terms— **Forestry, Fuzzy logic, Fisheye photography, Image classification, Image texture analysis**

I. INTRODUCTION

Remote-sensing estimates of forest structural variables need to be validated by means of reliable methods of in situ measurement [1]. Hemispherical photography can be used to this end, but its accuracy is affected by the light condition, which limits its use for large-scale sampling [2]. Also, the results are highly sensitive to both the camera exposure [3] and the classification procedure [4], which together compromise the robustness of the method.

Unlike devices as the LAI-2000, which measure transmittance and assume it equal to the gap fraction (GF), hemispherical photography allows the direct measurement of the GF [5]. The importance of GF data is that they allow estimating other canopy structural characteristics indirectly [6]. Canopy gaps refer to spaces in the canopy that could be pierced with a thin rectilinear probe (or light beam) without any contact with plant elements until reaching a point on the ground [7, 8]. GF is often defined as the fraction of unobstructed sky seen from beneath the canopy [9]. Nevertheless, because GF can also be measured by looking

downward from above the canopy [5], a broader definition is needed. Considering the sky and the ground as backgrounds for the plant element, here we defined GF as the fraction of background contained on the projected image plane over a given area defined by zenith and azimuth angles of view.

Extracting GF from photos requires the classification of each pixel as gap or nongap. The standard procedure is global thresholding, a simple image-processing technique that works properly with images that have two high-contrast features [10]. Global thresholding consists in setting a threshold value that segments the image in two classes. In upward-looking hemispherical photographs, the traditional premise is that, in the blue channel, sky pixels look brighter than plant pixels. Thus, the standard method is to set a gray threshold value in the blue that separates the dark from the light pixels. To take a photograph whose brightest pixels are only sky pixels, it is important that direct or reflected light does not reach the plant surface facing the camera lens. Thus, it is recommended to proceed when the sky is fully clouded or at dawn/dusk.

With nondiffused light, plant pixels can be as bright as sky pixels, a fact that leads to overestimating errors on GF. Sunlit canopy is an extreme case of this phenomenon: it can be observed when direct light reaches any canopy surface facing the camera lens [11]. Another process that can deliver solar radiation to the plant surface facing the lens, and so make it brighter, is multiple scattering from both the canopy element and the forest ground [12]. This light-condition dependency decreases the number of annual hours in which the photographs can be taken. Since this is taken as a weakness of the methodology, researchers have tried to find solutions with statistical modeling [2] and other technologies such as terrestrial laser scanners [13]. An alternative approach is to develop an image-processing method that does not require a bright background and dark plants or vice versa. In such a case, it is necessary to take into account that error sources, such as vignetting, blooming, and chromatic aberration, can also be found in image formation. Vignetting is a geometric-mechanic phenomenon that obscures off-center pixels [14, p. 114]. Blooming produces an increase in the brightness of the pixels that are around saturated ones [11]. Chromatic aberration is a color distortion linked with the optical properties of the lens, which can produce color fringes along the borders of photographed objects [15].

Techniques to minimize errors on GF data estimation have

been proposed as alternatives to global thresholding. Jonckheere et al. [1] proposed to extract the brightness profile from the blue channel at a zenith angle of 57.3° for the whole azimuthal range and process it with derivative analysis. In contrast, the approach of Schwalbe et al. [16] is based on image processing at pixel level. An alternative approach to the traditional pixel paradigm is object-based image analysis (OBIA), which is a sub-discipline of image analysis concerned with automatic object recognition [17]. Although OBIA has not been used to process hemispherical photography of the forest canopy, it has been used in maize fields with promising results [18].

Our objective was to develop an algorithm to classify hemispherical photographs with the aim to reduce errors in extracting GF data, such as errors produced by: sunlit canopy, multiple scattering, vignetting, blooming, and chromatic aberration. To aid in the development of the algorithm, photographs were acquired in a broadleaf forest. Section II describes the algorithm; Section III describes how the photographs were taken and processed, and how they were used to develop the algorithm; and Sections IV and V respond to conventional paper structures.

II. Description of the Algorithm

A. Color-based Enhancement Algorithm

Color has three different perceptual attributes: hue, lightness, and chroma. We propose to use these attributes to enhance the contrast between the sky and plants through fuzzy classification. Our premise is that the color of the sky is different from the color of plants. We propose the next classification rules, here expressed in natural language: clear sky is blue and clouds decrease its chroma; if clouds are highly dense, then the sky is achromatic, and, in such cases, it can be light or dark; everything that does not match this description is not sky. These linguistic rules can be translated to math language by means of fuzzy logic [19].

To calculate the membership to Sky-blue and Light, we used both fuzzy logic and the standard of the International Commission on Illumination (CIE) for colorimetric measurement, in particular the CIE 1976 (L*, a*, b*) color space, referred to as CIELAB. This is a tridimensional space defined by the axes lightness (L*), red-greenness (a*), and yellow-blueness (b*). The JPEG image format uses the standard red, green, and blue color space (sRGB). The main differences between these color spaces are that 1) CIELAB allows isolating the lightness from the other components of the color, and 2) the Euclidean distance between colors in the CIELAB space is linearly proportional to the perceived difference [14]. The translation of a picture from the sRGB to CIELAB color space produces an image with L*, a*, and b* channels.

To model the Sky-blue class, we used the Gaussian membership function and the channels a* and b*. In the supplementary material, we show examples of the Gaussian membership function in the ColorBased_Enhancement_Algorithm.html file.

The Light class required more complex modeling than the Sky-blue class. The greatest contrast on gray levels between the sky and the plants should be observed in the blue channel because sky scattering is relatively high in the higher frequencies of light, and so the blue channel ensures the brightest sky pixels. Nevertheless, in the blue channel, the interface between the sky and the foliage pixels can be as bright as sky pixels. These pixels look dark cyan colored instead of green. The color distortion observed should be linked with: color formation through color filter array [14, p. 271] and chromatic aberration [15]. These phenomena may be related to that reported by Jonckheere et al. [4], who stated that "the smallest vegetation elements might be invisible in the blue channel, especially during blue sky conditions." Thus, we propose to use an original feature that we denominate Relative Brightness (reBr) (1) instead of one-channel brightness:

$$reBr = \left(\frac{0.5R+1.5B}{2}\right)mSkyBlue + B(1-mSkyBlue) . \quad (1)$$

where R is a red channel value, B is a blue channel value, and mSkyBlue is the membership to the Sky-blue class.

To calculate the membership to the Light class, we propose to obtain a threshold value with the reBr feature and the algorithm of Ridler and Calvard [10], and to use the threshold value as the location parameter of a logistic membership function whose scale parameter depends on mSkyBlue. This dependence can be explained as follows: if mSkyBlue is equal to 1, then the membership function is as a threshold function because the scale parameter is 0; lowering mSkyBlue increases the scale parameter, thus blurring the threshold because it decreases the steepness of the curve.

All these operations were implemented in the color-based enhancement algorithm. The result of this algorithm is a synthetic band in which the original RGB-blue-light pixels have the highest digital number. This band is obtained by multiplying the membership to Sky-blue by the membership to Light. In the supplementary material, we included the ColorBased_Enhancement_Algorithm.html file to complement the explanation of this algorithm.

B. Segmentation Algorithm

Digital image segmentation, in a broad sense, is grouping pixels that go together. The raster structure of digital images is suitable to model regular interval measurements over a Cartesian space of two dimensions. Chessboard, one of the most straightforward segmentation algorithms, works by joining pixels but keeping their regular interval structure.

The regular interval measurements performed in hemispherical photography are over a polar space because the GF is linked, by definition, with the line of sight determined

by the azimuth and zenith angles. For example, the segmentation can be done with 5° to produce 18 zenithal rings and 72 azimuthal sectors, i.e. a total of 1296 segments (hereafter referred to as sky map segmentation).

The quad-tree segmentation algorithm is also straightforward: it makes recursive divisions in four equal parts until the homogeneous criterion is reached and then stops locally. As in chessboard, the usual implementation of the quad-tree algorithm is based on the raster structure, and this is why the resultant objects are squares of different sizes. We propose to implement the quad-tree segmentation in a polar space (hereafter referred to as polar quad-tree segmentation). In the supplementary material, we included the Segmentation_Algorithm.html file to complement the explanation of this algorithm.

Fig. 1. Pixel level classification using features related to classes from Level +1.

C. Algorithm of Object-based Image Analysis

The OBIA strategy that we implemented can be exposed as classification-segmentation sequences, as follows:

1) *Classification of Level 0 (pixels)*
This step consists in automatically binarizing a hemispherical photograph preprocessed with the color-based enhancement algorithm and classifying it by assigning the class Gap-candidate to pixels above the threshold and the class Plant to the rest of unclassified pixels. We used the Gap-candidate class to semantically state the potential GF overestimation.
2) *Segmentation of Level +1 (objects)*
The result is a sky map with one degree angular resolution.
3) *Classification of Level +1*
This step consists in assigning the class Mix-OR-Gap to segments with GF greater than 0 and the class Plant to the rest of unclassified segments.
4) *Segmentation of Level +1*
This step consists in a polar quad-tree segmentation of the blue channel and intersecting the segmentation with a binary mask of the pixels that were classified as Plant.
5) *Classification of Level +1*
This step has two stages: automatic selection of samples and sample-based classification. In the first stage, the brightness of the blue channel is used, whereas in the second stage, only Haralick textures are used. These textures are calculated with both the blue and red channels, but separately.
   We assumed that texture is more effective than brightness to discriminate between pure gap objects and gap-canopy objects only if the canopy is affected by sunlit canopy, multiple scattering, vignetting, blooming, and chromatic aberration, in any combination. Using texture implies

dealing with its strong dependence on the sun-sensor-object geometry. To overcome this difficulty, we used sample-based classification. To this end, we assumed that blue channel brightness is effective to identify a set of representative samples. The result is objects labeled either Gap or Mix.
6) *Classification of Level 0*
This step consists in a pixel-level classification using features that are related to the class of Level +1 (Fig. 1).
7) *Segmentation of Level +1*
This step is a reshape that produces smaller objects by intersecting Level +1 with a binary mask of the pixels that were classified as Gap-candidate at Level 0.
8) *Classification of Level 0*
This step consists in a regional automatic thresholding whose region is delimited with pixels that were classified as Gap-candidate at Level 0. The thresholding uses the feature superobject ratio of L* (Ratio$_{L*}$) (2)

$$Ratio_{L*} = L*_i / L*_{mean} . \quad (2)$$

where L*$_i$ is the value of pixel i on channel L*, and L*$_{mean}$ is the L* object-mean value of the superobject from Level +1 to which pixel i belongs. The threshold is calculated with the algorithm of Ridler and Calvard [10]. The classification is finally performed by assigning the class Gap to pixels above the threshold and the class Plant to the rest of unclassified pixels inside the Gap-candidate region.
   Finally, the class Plant obtained in step 1 is added to the classes Plant and Gap obtained in step 8, and all the pixels classified as Saturated are assigned to Gap.

In the supplementary material, we included the OBIA_Algorithm.html file with complementary figures.

III. MATERIALS AND METHODS

Five sampling sites were selected in a broadleaf stand of *Nothofagus pumilio*, in the South of Argentina (Northwest of the province of Chubut, 43 ° 49´ S, 71 ° 28´ W). The selection was done in the field by visual analysis of the canopy cover (the proportion of horizontal vegetated area occupied by the vertical projection of canopy elements). The aim of the selection process was to avoid the inclusion of sites with similar canopy cover[1].

At each selected site, we installed a permanent structure to support the photographic equipment (with the optical axis oriented to the local zenith and pointing upward). The structure allowed us to take quick multiple photographs with the same viewpoint but on different days and at different times. We used the Nikon FC-E9 converter attached to the Nikon Coolpix 5700 camera. This equipment allows obtaining circular fish-eye photographs with equidistant projection. We

[1]In the supplementary material named Reference_Data.zip, we include the color photographs and the binarized images used as reference data.

set up the camera to store high-quality JPEG pictures, and thus acquire hemispherical images with 1596 pixels in diameter.

The photographs were taken between December 5 and December 9, 2009. The weather was stable, with mild breezes and low cloud cover. Photograph acquisition was organized in series of five photographs at one picture per site rate. The sites were chosen along a transect with at least 20 m between the nearest sites. With this spatial configuration, completing each series demanded about 10 min. This time constraint was fixed to minimize the variation in the daylight during each set of photographs. To minimize the effect of topography, we chose the forest in a relatively flat 250-m area. To follow the protocol of Zhang et al. [20], we made sure that the whole sampling site had a nearby gap to take the automatic exposure without obstructions, at least from nadir to 75°. A few seconds before starting the photograph acquisition and only once per series, the exposure was estimated with the protocol of Zhang et al. [20] with two stops of overexposure above the reference.

The photographs were taken in three different conditions: 1) during dawn and dusk (diffused light) and determining the exposure with the protocol of Zhang et al. [20]; 2) with diffused light and determining the exposure automatically with the centrally weighted average mode; and 3) with nondiffused light and determining the exposure automatically with the centrally weighted mode. We took a total of 75 photographs at a rate of five series per mode (25 photographs per mode and 15 per sampling site).

The photographs were used to assess different strategies of image analysis for algorithm development. The assessment was the comparison of the accuracy of the OBIA algorithm versus that of the standard procedure. The latter consisted in the automatic global thresholding of the blue channel with the algorithm of Ridler and Calvard [10]. The selection of this procedure was based on [4]. To calculate accuracy, we used the difference between the reference GF and the estimated GF, i.e., error. The estimated GF was extracted from: 1) the images processed with the OBIA algorithm, and 2) the images binarized with the standard procedure.

The reference GF was obtained following these steps: 1) the highest contrast series was selected through visual analysis of the photographs acquired with diffused light and the protocol of Zhang et al. [20], where by "contrast" we mean the difference between sky and plant brightness; 2) for each of the five photographs of the chosen series, we performed a global interactive (manual) thresholding of the blue channel with the original color photographs as visual reference; and 3) the GF was obtained with the binarized images.

The Total GF was calculated with the CLMPML program of the CIMES package [6] and with image area between 30° and 60° zenith angle [21]. To compare between the estimated and the reference GF at the segment level, we used the GFA program of CIMES. The program was set to extract GF with 9 rings and 36 sectors. This setting performs segmentation with 10° of angular resolution. This analysis was done with image

Fig. 2. Comparison between the OBIA algorithm and the standard procedure at the segment level. Each point represents a sky segment of 10° zenithal angle by 10° azimuthal angle. There is no distinction between images. GF = Gap fraction; (Non-) Diffused = photos were taken with (non-) diffused light. Solid lines are second-order polynomial models. IQR = interquartile range of the model residuals. Dashed line is 1:1 relationship. All photos were taken with auto-exposure.

segments between 30° and 60° zenith angle [21].

We used R [22] to program the algorithm and to perform all mathematical, statistical, and graphical operations. The script uses colorspace [23], raster [24], pracma [25], EBImage [26], and class [27] packages. The standard binarization was carried out with the Ridler and Calvard [10] algorithm implemented in ImageJ. We used Welch Two Sample t-tests to compare error means (0.05 alpha).

IV. RESULTS AND DISCUSSION

A. Error Analysis at Image Level

The reference Total GF ranged from 0.110 to 0.230. The Root Mean Square Error (RMSE) of the Total GF was 0.208 and 0.076 with diffused light, and 0.245 and 0.076 with nondiffused light. In both cases, the greatest RMSE was that of the standard procedure, whereas the lowest RMSE was that of the OBIA algorithm. The statistical significance of this difference was verified (diffused: $t = -11.6905$, $df = 45.476$, p-value = 2.675×10^{-15}; nondiffused: $t = -10.9771$, $df = 38.168$, p-value = 2.269×10^{-13}). The normality of errors was tested with Shapiro-Wilk test. Nevertheless, at image level, we were not able to evaluate whether the error estimation was affected by the self-cancellation of errors from different areas of the hemisphere.

B. Error Analysis at Segment Level

Figure 2 shows the differences between the classification procedures at the segment level, in which it can be seen that the GF extracted from images processed with the OBIA algorithm are closer to the 1:1 line than the GF extracted from images binarized with the standard procedure. Nevertheless, a bias of overestimation is observed in all cases. The interquartile range (IQR) of the model residuals is lower for the OBIA algorithm than for the standard procedure. A lower IQR indicates less self-cancellation. In conclusion, the analysis at segment level confirms that the significant difference between the OBIA algorithm and the standard procedure was not artificially produced by self-cancellation. Thus, this suggests that the OBIA algorithm may be more exact than the standard procedure.

C. Discussion

The same data used for the development of the algorithm

was used for the analysis of errors. However, it is important to note that the algorithm is fundamentally a nonstatistical approach designed with general principles of image analysis. The results demonstrate that OBIA is an effective way to use color and texture dimensions for hemispherical photograph analysis. The advantage of the OBIA algorithm over the method proposed by Jonckheere et al. [1] is that the former allows analyzing more amplitude of zenith angle. The method proposed by Schwalbe et al. [16] does not deal with errors produced by direct solar radiation, which is a disadvantage in contrast with the OBIA algorithm. However, the method proposed by Schwalbe et al. [16] allows subpixel estimation, which could be considered as an advantage if low-resolution images are used [28] but not when working with current high-resolution equipment [29]. Our results confirm that the standard procedure with diffused light and automatic exposure overestimates GF. Although we obtained promising results using the OBIA algorithm with automatic exposure, future works should evaluate if better accuracy can be obtained with other exposure-determination procedures.

V. Conclusion

Here, we proposed an algorithm to preprocess hemispherical photographs whose aim is to reduce errors in the extraction of GF data. The target errors are those produced by sunlit canopy, multiple scattering, vignetting, blooming, and chromatic aberration. We based the algorithm on general principles for the sake of robustness. The script was developed with free software and can be downloaded without restriction under the GPL 3 license from the supplementary material. In future works, it will be necessary to assess the algorithm performance with independent data, acquired in other forest ecosystems with other hemispherical photograph equipment. To this end, we recommend the sampling design presented in this work.

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