

BATCH PROCESSING OF HEMISPHERICAL PHOTOGRAPHY USING OBJECT-BASED IMAGE ANALYSIS TO DERIVE CANOPY BIOPHYSICAL VARIABLES

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KEY WORDS: digital hemispherical photography (DHP), leaf area index (LAI), batch processing, maize, CAN-EYE

ABSTRACT:

Hemispherical photography has received renewed interest to describe plant canopies and measure canopy gap fraction from which important biophysical variables such as leaf area index (LAI) can be derived. This kind of remote sensing imagery is typically processed by setting a threshold on the histogram of a given image feature to segment the image and separate target from non-target pixels. Selecting such a threshold can be complicated due to varying image acquisition conditions and to the difficulty of defining canopy gaps. Having an operator who individually analyses images can be prohibitively time consuming for some applications, such as validating LAI products retrieved from satellite remote sensing where large numbers of samples are necessary. This paper presents how object-based image analysis can be applied to digital hemispherical photography in order to estimate automatically biophysical variables in a batch mode using the dedicated software CAN-EYE. The method is demonstrated by applying it to 114 sets of images obtained over 30 maize fields visited at several dates along the 2009 crop growing in Belgium and the Netherlands. The results obtained by the automatic method are comparable to those obtained by manual processing using CAN-EYE and this holds for DHPs acquired at different maize growth stages and with different viewing configurations. These encouraging results indicate object-based segmentation approach has great potential to provide efficient and automated solutions for hemispherical photography.

1 INTRODUCTION

The role of plant canopies in the terrestrial ecosystems cannot be undermined. Photosynthesis, transpiration and energy balance are all related to the quantity of green foliage within these canopies. Many agronomic, ecological and meteorological applications require information on the status of plant canopies by way of biophysical variables. Leaf area index (LAI) is amongst the most frequently used. It is defined as half the total developed area of green leaves per unit ground horizontal surface area (Chen and Black, 1992). Other biophysical variables of interest are the fraction of ground surface covered by green vegetation (FVC) and the fraction of absorbed photosynthetically active radiation (FAPAR). Remote sensing has proven to be an invaluable tool to estimate biophysical variables over large extents at a frequent rate. However, in situ measurements are ultimately necessary to calibrate and validate remote sensing products.

LAI measurement procedures are either direct or indirect (Gower et al., 1999, Bréda, 2003, Jonckheere et al., 2004). Direct methods generally involve destructive harvesting techniques and litter fall traps. While they are extremely time-consuming and labour-intensive, direct methods are more accurate and thereby serve as reference for more pragmatic indirect approaches. Indirect methods rely on measuring the gap fraction of the canopy, or the probability of a light ray missing all foliage elements while passing through the canopy (Gower et al., 1999, Weiss et al., 2004). Gap fraction can be measured using several dedicated commercial instruments (e.g. LAI-2000 and AccuPAR) or by deriving it from hemispherical photography. Digital hemispherical photography (DHP) are obtained from a camera with a mounted hemispheric (fish-eye) lens pointed either upwards towards the sky from beneath the canopy or downwards from a position above the canopy. The result is a wide-angle colour image of the canopy from which green plant tissues can be identified (see figure 1). Compared to other indirect LAI measuring techniques, DHP have proven to be more robust (at least over croplands) by having a low sensitivity

to illumination conditions and by providing an accurate spatial sampling of gap fraction (Garrigues et al., 2008).

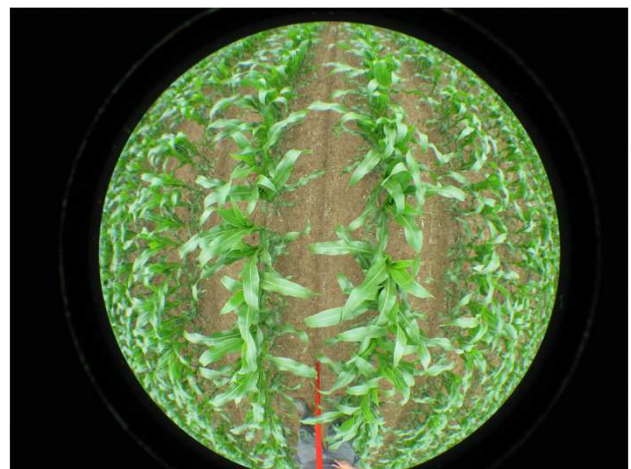


Figure 1: Example of a digital hemispherical photograph taken from above a maize canopy in the downwards configuration

To derive canopy gap fraction from DHPs, green plant elements need to be identified and isolated from the rest of the image. This step is the most critical to accurately retrieve LAI from the pictures. Several software propose an interface allowing a user to set a threshold on some colour or index in order to achieve this classification operation. Selecting such a threshold can be complicated due to varying image acquisition conditions and to the difficulty of identifying canopy gaps, especially when looking downward on dense canopies. To validate remote sensing products, important field campaigns with a large set of samples are often necessary and images are sometimes acquired in sub-optimal conditions (e.g. direct instead of diffuse light, inadequate contrast). To ensure that measurements can be taken over a large geographic extent, it might be necessary to dispatch several teams on the field simultaneously, each with a measuring unit (camera

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+ lens) which may be of lower quality due to budget constraints. A reduction in the quality of both the camera (increasing noise) and the hemispheric lens (which might have stronger chromatic aberration) reduces quality of the DHP, thus complicating gap fraction estimation (Inoue et al., 2004). Having an operator who individually analyses images can be prohibitively time consuming and heavily dependent on the operator's subjectivity. Under all these conditions, a reliable and robust automatic method to classify DHPs is definitely interesting.

The motivation of this research is to explore how object-based image analysis can be used to overcome the above-mentioned problems. A classification method of DHPs is proposed that couples multiresolution segmentation with a transformation of the colour space to produce binary masks which delineates the green vegetation elements from the rest of the photograph. Such binary masks can then be ingested in DHP processing software with a batch mode in order to provide biophysical variables such as LAI from large amounts of images.

2 MAIN BODY

2.1 Theoretical Background

After reviewing and testing many different automatic thresholding algorithms for DHPs, Jonckheere et al. (2005) concludes that there is still room for improvement and that new and more complex algorithms are necessary, especially to smooth the images and remove noise. Whether it is automatic or manual, DHP thresholding is a type of image segmentation. The division of the image in segments is generally based on grey-level histograms computed on the entire pixel population. This neglects the spatial adjacency of the pixels corresponding to the target vegetative elements and may lead to 'salt-and-pepper' effects. Some thresholding methods exploiting the spatial dependency of pixels in a neighbourhood (Abutaleb, 1989) have been shown to perform well on DHPs (Jonckheere et al., 2005). However, an approach where spatially adjacent and spectrally similar pixels are grouped in image-objects before applying thresholding (as it is done in object-based image analysis) has never been applied to DHP to our knowledge. In this paper, the multiresolution segmentation algorithm (Baatz and Schäpe, 2000) implemented in Definiens Developers 7 software (Definiens, 2008) is tested on DHPs. It has the advantage of being repeatable, applicable on multivariate imagery and sensitive to the shape of the studied objects.

Most of the literature on thresholding DHPs is focused on upward looking imagery acquired under forest canopies. Under these conditions, the 3 camera channels (RGB) are highly correlated and typically only one is used. Attention is placed on images obtained in both upward and downward configurations for lower canopies such as crops. When looking downward, gap fraction estimation is more problematic because (i) the soil background is generally less homogeneous than the sky and (ii) lower vegetation elements are difficult to discriminate when overshadowed by the higher leaves. On the other hand, when looking downward the 3 RGB channels can be exploited to separate green vegetative elements from the soil background. Complications arise for setting thresholds when illumination conditions vary. To mitigate these effects, the RGB colour space can be transformed to different projections in order to achieve optimal separation of vegetation elements from the rest of the image (Panneton and Brouillard, 2009). For example, Kirk et al. (2009) uses the red and green channels to derive greenness and intensity indicators to better classify vegetative elements to estimate LAI from (non-hemispherical) imagery.

2.2 Methodology

DHPs were acquired various maize fields in Belgium and the Netherlands at different stages along the 2009 growing season. The visited fields are distributed within 3 different agro-ecological regions: (1) the *Hesbaye* region in central Belgium, dominated by agricultural land use given its high soil fertility; (2) the *Condroz* region, located south of the former and characterized by a more variable topography of alternating plateaus and valleys; and (3) the *Flevoland* polder in central Netherlands which consists of fertile and flat recovered land.

To test cost-effective conditions, the measuring equipment is composed of a low-cost Canon PowerShot A590 camera mounted with a Besel Optics wide angle lens allowing an effective field of view of 60° . The resulting image size is 2448 by 3264 pixels. Images were acquired using both downward and upward looking configurations. When looking downwards, the camera-lens system is attached to a pole in order to take pictures at about 1 m above the top of the canopy. A minimum of 8 pictures are taken within a range of about 50 by 50m for every visited field. Each set of DHPs constituted in this way is supposed to represent the canopy's variability (Weiss et al., 2004) and will produce a single value for a given biophysical variable. A total of 30 fields were visited at various dates along the season to result in 114 sets of DHPs images.

As mentioned before, the object-based image analysis is realized using Definiens Developer 7 software (Definiens, 2008). Since the multiresolution algorithm runtime is roughly proportional to the number of image object mergers, most computing time is spent to create rather small image objects of 2-4 pixels (Definiens, 2008). To accelerate the multiresolution segmentation, the first processing step is a quadtree segmentation which divides the image into elementary squared units which do not necessarily have the same size (see fig 2b). Two features are then calculated for each object based on the mean object value of the 3 RGB channels. The first is hue, which is a gradation of colour defined as:

$$H = \begin{cases} 60^\circ \cdot \frac{G-B}{MAX-MIN}, & \text{if } MAX = R \\ 60^\circ \cdot \frac{B-R}{MAX-MIN} + 120^\circ, & \text{if } MAX = G \\ 60^\circ \cdot \frac{R-G}{MAX-MIN} + 240^\circ, & \text{if } MAX = B \end{cases} \quad (1)$$

where the R, G and B are the red, green and blue channels expressed as numbers from 0 to 1, and MIN and MAX are respectively the smallest and the greatest of the RGB values. The resulting value of hue, H , is a position in the colour wheel expressed in degrees. The interest of the transformation is that hue provides colour information which is independent of the illumination conditions. The second feature is simply the ratio between the green and red object mean values which has already been used to discriminate between green plant tissue and soil (Kirk et al., 2009). Once these features are calculated for each squared object, a multiresolution region growing algorithm is applied based on R, G and H . A scale parameter of 10 was chosen. The homogeneity criterion is conditioned by shape at 20%, which itself is divided evenly between compactness and smoothness (Definiens, 2008). The resulting objects (see fig 2c) can then be classified based on their mean H and G/R values to yield a binary classification (see fig 2d). In this case, the classification is based on membership functions over the H and G/R features which were obtained using a sample set of objects from several different images.

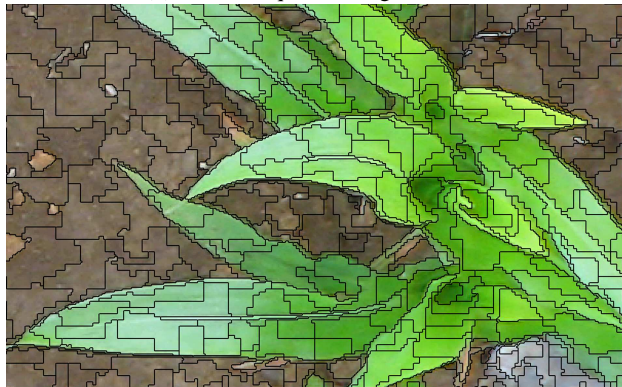
The calculations required to derive canopy structure information from gap fraction are performed using a dedicated free software called CAN-EYE (http://www.avignon.inra.fr/can_eye). CAN-



(a) Subset of the input image



(b) Result of quadtree segmentation



(c) Result of the multiresolution segmentation



(d) Final binary classification

Figure 2: Illustration of the automatic processing on a subset of an hemispherical photograph taken over maize from above the canopy.

EYE differs from other DHP software by calculating other biophysical variables besides LAI, such as FVC and FAPAR. The input is a set of either RGB images (in manual mode) or binary mask (in batch mode). When using CAN-EYE interactively (RGB images), it is possible to discard undesirable images or part of images (e.g. due to sun glint). In the batch mode, such images need to be screened out before the processing outside of the CAN-EYE environment. It is worthwhile to mention that when used in the interactive mode, the software applies an automatic colour segmentation in which the total numbers of distinctive colours is reduced to 324. This reduction of the radiometric resolution simplifies the subsequent manual thresholding operation. An extra advantage of CAN-EYE that enables the use of lower quality optics is that it has an integrated module to calibrate the measuring instrument (camera + fisheye system) by finding the optical centre's coordinates and estimating the projection function.

2.3 Results and Discussion

The method is validated by comparing the results with those obtained using CAN-EYE interactively. Two different users processed the same 15 image sets. Six extra sets, processed by a third operator, are also included in the validation set. The confrontation of interactive versus automatic results is shown on figure 3. Overall, the automatic results provides comparable results when confronting them to those obtained interactively for the 3 biophysical variables (LAI, FVC and FAPAR) and for both upward and downward configurations. The automatic method does yield higher estimations for LAI and FAPAR when canopies with low biomass are examined. This suggests that gap fraction is systematically underestimated early in the growing season when canopy cover is low. Further fine-tuning might be necessary to ensure that the classification is unbiased in these circumstances.

Validation with interactive use of CAN-EYE is not feasible for all 114 sets of images. However, since the DHPs were acquired at different times along the season, an idea of the estimation quality can be inferred by looking at the temporal consistency. This is illustrated in figure 4. For the sake of clarity, this figure only presents the mean and standard deviation of all LAI estimations in a region at a given time. Although the estimations might not be ideally distributed in time (i.e. fields could have been more frequently visited, especially in FlevoLand), a difference between the 3 regions can already be noticed. For example, the regional LAI growth curve for *Condroz* is slightly shifted towards later dates compared to the *Hesbaye* curve.

An expected improvement in the thresholding quality by using the automatic method comes from removing the salt-and-pepper effect that can occur while classifying manually. As seen on figure 5, such risk is eliminated under an object-based approach since the classification is performed on the mean object values instead of individual pixels. This approach has the advantage to remove noise like a smoothing operation would do, but without the disadvantage of blurring the edges.

3 CONCLUSIONS AND PERSPECTIVES

This paper presents how object-based image analysis can be applied to digital hemispherical photography in order to estimate automatically biophysical variables in a batch mode using the dedicated software CAN-EYE. The demonstration on DHPs acquired on maize canopies with both downward and upward configurations shows that the results obtained by the automatic method are comparable to those obtained by manual processing. This observation seems to hold at different growth stages along the

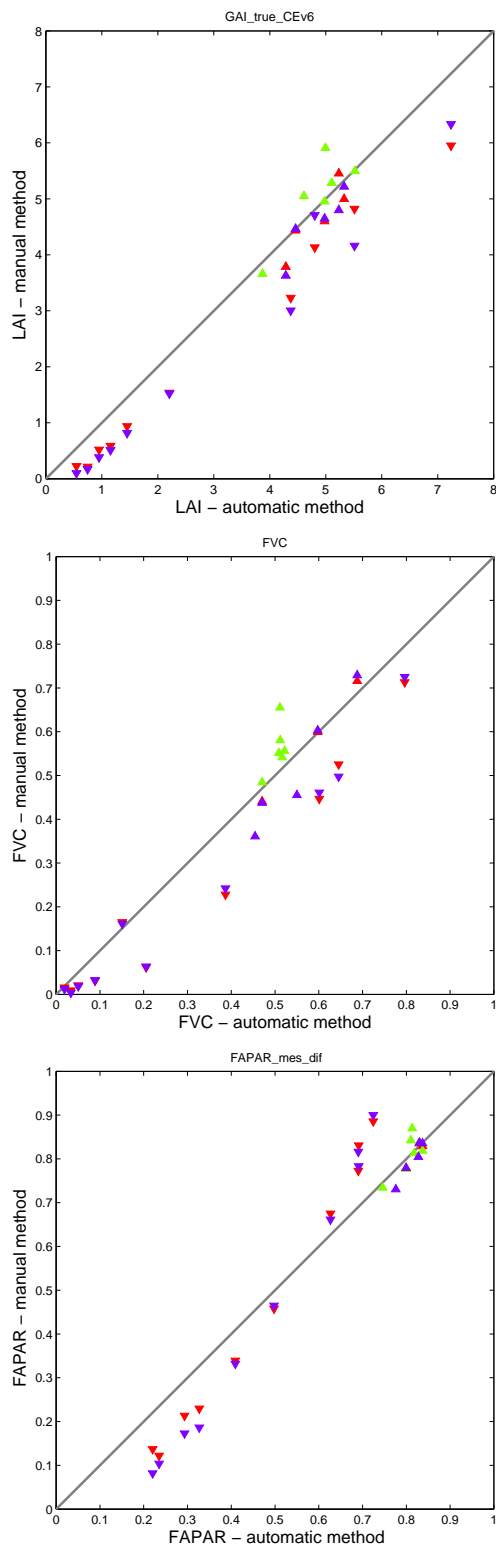


Figure 3: Confrontation of biophysical variables obtained using the automatic methodology against those obtained by different interpreters (one per marker colour). Triangles pointing downward (upward) represent results from digital hemispherical photography acquired looking downward (upward) towards the canopy. The biophysical variables assessed here are green area index (top), fraction of vegetation cover (middle) and fraction of absorbed photosynthetically active radiation (bottom).

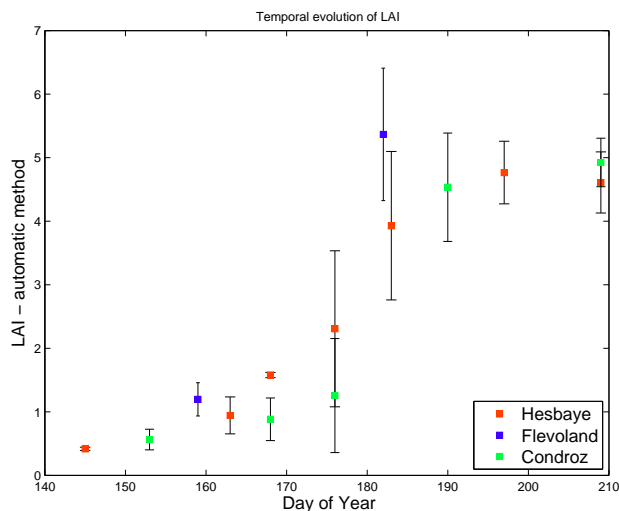


Figure 4: Temporal evolution of regional LAI estimations along the crop growing season within the 3 different study zones. The mean and standard deviation of all LAI estimations is resumed at a given time and for each region.

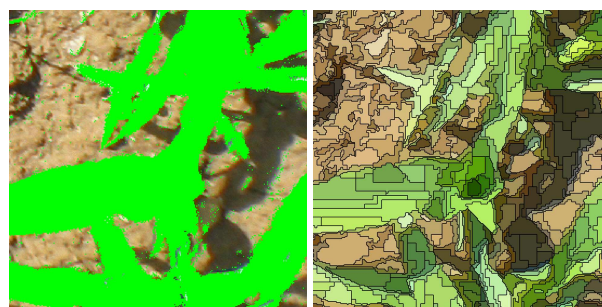


Figure 5: The salt and pepper effect potentially present when thresholding based on the histograms (left) is avoided when objects are first delineated (right).

season, albeit some improvements need to be addressed to avoid underestimation of gap fraction in the early stages. The applicability of the approach to other crops still needs to be investigated. Whereas delineating other broadleaved crops should be straightforward, working on dense cereal canopies is certainly not so trivial due to smaller leaf size and more ambiguity in gap fraction definition (e.g. overshadowed lower leaves can be mistaken for bare soil).

In a domain that is largely been dominated by image segmentation using histogram thresholds, object-based segmentation approach has great potential to provide efficient and automated image processing solutions. Although the approach presented here already provides encouraging results, it must be reckoned that object-based analysis is used in a very simple way leaving much room for improvement and fine-tuning. For example, the membership functions used to classify the object are obtained by empirical sampling in a series of images. This manual operation could easily be replaced by totally automatic approach by first identifying some objects with strict and reliable default membership functions and then use region growing segmentation algorithms. Such alternation between segmentation and classification could also be employed to refine delineation of leaves. Improvements could also come from using a more adapted colour space to differentiate vegetation from non-vegetation.

ACKNOWLEDGEMENTS

This research was funded by the Belgian *Fond National pour la Recherche Scientifique* (FNRS) by way of a PhD grant to the first author. The research also falls in the framework of the GLOBAM project which is financed by the Belgian Scientific Policy (BEL-SPO) with the STEREO II programme. The authors would like to thank Marie Weiss for her comments on the manuscript and for her help using CAN-EYE. Further thanks go to Yannick Curnel and Emilie Bériaux who processed some validation images with CAN-EYE.

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