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Calibration of hyperspectral close-range pushbroom cameras for plant phenotyping

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ABSTRACT

Hyperspectral sensors are able to detect biological processes of plants which are invisible to the naked eye. Close-range cameras in particular support the identification of biotic and abiotic stress reactions at an early stage. Up to now, their full potential is only partially realized because geometrical factors as leaf angle, curvature and self-shading, overlay the signal of biological processes. Suitable 3D plant models constitutes an important step to removing these factors from the data. The matching of these 3D model and the hyperspectral image with sufficient accuracy even for small leaf veins is required but relies on an adequate geometric calibration of hyperspectral cameras.

We present a method for the geometric calibration of hyperspectral pushbroom cameras in the close-range, which enables reliable and reproducible results at sub-pixel scale. This approach extends the linear pushbroom camera by the ability to model non-linear fractions. Accuracy and reproducibility of the method is validated using a hyperspectral senor system with two line cameras observing the reflected radiation in the spectral range from 400 to 2500 nm. We point out new potentials arising from with the proposed camera calibration, e.g. hyperspectral 3D plant models, which have high potential for crop plant phenotyping.

1. Introduction

Hyperspectral imaging is an established technique for land-cover classification and the separation of varieties in remote sensing (Thenkabail et al., 2012). In close-range setups it is used to detect stress processes and defense reactions of single plants (de Jong et al., 2012; Mahlein et al., 2012; Sun et al., 2011). As hyperspectral imaging is able to detect deviations in plant-physiological parameters non-invasively, it is an important sensor for high-throughput phenotyping. In this approach, a large number of plants are observed to describe phenotypical characteristics resulting from the interaction of genotypes with various environmental conditions. The importance of an accelerated and automated phenotyping of plants has grown significantly in recent years (Furbank and Tester, 2011).

The signal recorded by hyperspectral sensors, however, is affected by several influencing factors, e.g. illumination, surface geometry and observation angle (Fig. 1, Bousquet et al., 2005). These factors are one of the reasons for the poor signal-to-noise ratio (SNR) in hyperspectral images as they overlay the signal of biological processes. For a remote sensing problem, Morton et al. (2014) recently showed impressively that MODIS (Moderate-resolution Imaging Spectroradiometer) images of the Amazonas region were misinterpreted, because the sun-sensor geometry was inadequately modeled. The impact of the geometry increases further in close-range scenarios including higher plants or entire crop stands with more complex geometry (Behmann et al., 2014). Experiments with the investigated sensor system and sugar beets suggests that more than 60% of the spectral information depends on plant geometry (Fig. 1).

Therefore, methods that focus on relevant parameters and fade out factors which are not related to plant characteristics under investigation are very important for an suitable data analysis.

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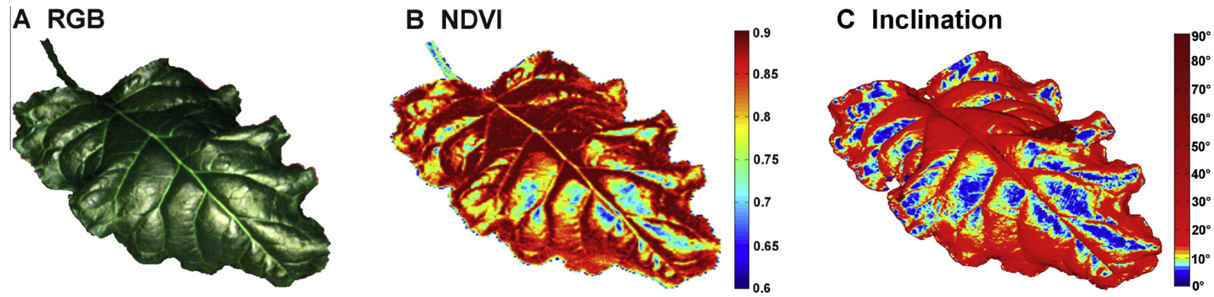

Fig. 1. The camera calibration uncovers the relation of reduced NDVI and horizontal leaf parts as it allows to combine automatically spatial and spectral information. (A) RGB image, (B) NDVI values and (C) the local inclination from a 3D plant model, calculated for each pixel of the hyperspectral image. The specular reflections are the result of the leaf geometry and not related to the physiological state of the plant.

1.1. Robust data analysis

In remote sensing, the hyperspectral signal is known to be affected by different illumination conditions and it is also assumed that the conversion to reflectance neglects some factors, e.g. cloud shadows and surface topography. Therefore, indicators were designed which are more robust against these factors and, consequently, reduce the effects on final results (Huete and Justice, 1999; Jensen, 2009). For this purpose, Vegetation Indices (VI) like NDVI (Normalized Differenced Vegetation Index) or PRI (Photochemical Reflectance Index) based on ratios of bands are used (Thenkabail et al., 2000; Broge and Leblanc, 2001). However, this approach has significant limitations as the indicators are only designed to be robust against specific, already known effects. The NDVI, e.g. is robust against variable brightness but non-Lambertian effects are not regarded (Matsushita et al., 2007). Therefore, the strong BRDF (bi-directional reflectance distribution function) effects are also visible in the NDVI (visualization in Fig. 1).

Alternatively, the strongest factors may be measured separately and their effect on the signal is modeled and can be removed from the observed signal subsequently. For example, BRDF models pursue this approach in remote sensing (Bousquet et al., 2005; Jacquemoud et al., 2009). The main drawback of physical modeling is, that the different factors have to be measured directly (Kuester et al., 2013). Simultaneously, it is generally impossible to deduce geometrical information from a single hyperspectral image. The 3D reconstruction from multiple hyperspectral images, regardless if they are observed by line scanners or area format cameras using Fabry–Perot interferometer (FPI) is not established up to now. However, high resolution 3D plant models are required and need to be related to the image for modeling the effect of the geometry on the hyperspectral signal.

1.2. Camera calibration

This connection between 3D model and recorded 2D hyperspectral image requires the description of the geometrical imaging characteristics of the sensors involved (Clarke and Fryer, 1998). In this context, camera calibration is defined as the process to derive a mathematical description of the geometric and radiometric characteristics of a camera (Clarke and Fryer, 1998). The calibration of the observed intensities, i.e. the calculation of reflectance, is common in a hyperspectral context. It includes the subtraction of the dark frame and ratio to a white reference (Grahn and Geladi, 2007).

For geometric camera calibration, a large number of methods has been published (e.g. Clarke and Fryer, 1998; Schowengerdt, 2006). Beneath models for central camera types with a single effective viewpoint, generalized models (Gennery, 2006; Kannala et al., 2009; Sturm et al., 2011) and models for line cameras (Horaud et al., 1993) were developed.

The default camera type are pinhole cameras, which can be parametrized by the focal length as interior parameter and the projection center and rotation matrix as exterior orientation. Common techniques for the determination of those parameters are the spatial resection (Haralick et al., 1994) and direct linear transformation (DLT, Abdel-Aziz and Karara, 1971).

In contrast, the geometric calibration of hyperspectral cameras in close-range applications has not yet been done, but is requisite for geometric calculations and radiometric analyzes in a phenotyping context.

1.3. Calibration of hyperspectral cameras

Hyperspectral sensors are often designed as line scan cameras that break down the spectral composition of a 1D pixel line onto a 2D CCD array, which records one spatial and one spectral dimension. Consequently, a 2D hyperspectral image is composed of consecutively recorded lines what has led to term pushbroom camera. For pushbroom cameras, every line of the recorded image is the result of a unique exterior orientation including projection center and rotation matrix. Therefore, the well established calibration methods for pinhole cameras are not applicable to pushbroom cameras. These cameras require specific approaches with an adapted set of camera parameters.

The line scan camera technique is common for observations from air- or spacecrafts and most publications about the calibration focus on this scale (e.g. Bezy et al., 1999; Kornus et al., 2000; Poli and Toutin, 2012). The biggest differences to close-range applications are the higher stability of the sensor trajectory and the availability of additional orientation information. Weser et al. (2007) introduced a generic pushbroom model for imaging satellites, which describes the movement of the satellite in an orbital coordinate system realized by splines. This sensor model was developed to be compatible with system parameters of many satellites as demonstrated for three different satellites. Hirschmüller et al. (2005) reconstructed 3D city scenes from images of a pushbroom camera using additional GPS/IMU measurements of the aircraft to model the non-linear movement of the sensor by spline approximation.

The calibration of 1D cameras for 3D reconstruction was investigated by Caulier and Spinnler (2004). They did not regard camera movement as they assume a fixed 1D pinhole camera and a moving object. Špiclin et al. (2010) focused the wavelength dependent spatial distortion of current hyperspectral pushbroom cameras. They represented the distortion by a wavelength-dependent cubic spline without assumptions on the distortion complexity. For this purpose, they represent the camera by a projective transformation between the imaged plane and the sensor plane. Their approach