Generation and application of hyperspectral 3D plant models

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Abstract. Hyperspectral imaging sensors have been introduced for measuring the health status of plants. Recently, they have been also used for close-range sensing of plant canopies with a more complex architecture. Th complex geometry of plants and their interaction with the illumination scenario severely affect the spectral information obtained. The combination of hyperspectral images and 3D point clouds are a promising approach to face this problem. Based on such hyperspectral 3D models the effects of plant geometry and sensor configuration can be quantified an modeled. Reflectance models can be used to remove or weaken the geometry-related effects in hyperspectral images and, therefore, have the potential potential to improve automated phenotyping significantly.
We present the generation and application of hyperspectral 3D plant models as a new, interesting application field for computer vision with a variety of challenging tasks. The reliable and accurate generation requires the adaptation of methods designed for man-made scenes. The adaption requires new types of point descriptors and 3D matching technologies. Also the application and analysis of 3D plant models creates new challenges as the light scattering at plant tissue is highly complex and so far not fully described. New approaches for measuring, simulating, and visualizing light fluxes are required for improved sensing and new insights into stress reactions of plants.

Keywords: hyperspectral, 3D scanning, close range, phenotyping, modeling, sensor fusion

1 Introduction

Hyperspectral images are an important tool for assessing the vitality and stress response of plants [1, 2]. In recent time, the sensor technology for hyperspectral plant phenotyping has improved in resolution, accuracy, and measurement time and is integrated into phenotyping platforms. However, the spectral signals are influenced by the geometric sensor configuration and the plant geometry. So far, these effects are not considered and also often neglected in data analysis and, therefore, increase the noise level.

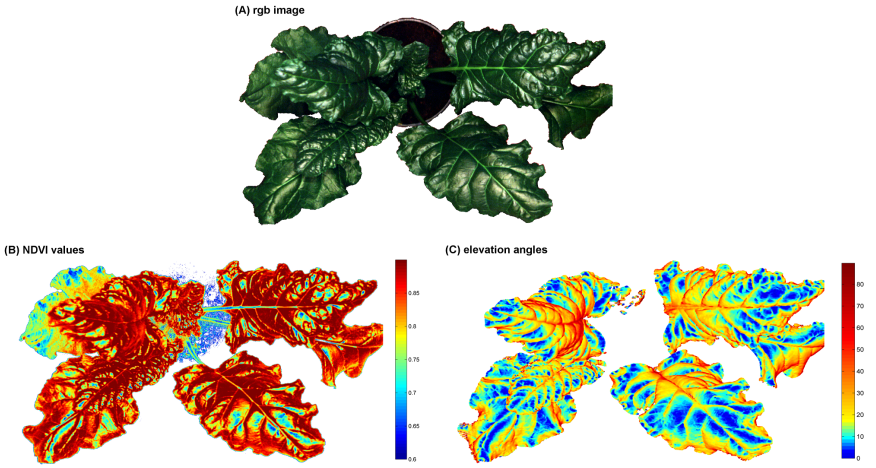

Fig. 1. The effect of plant geometry on spectral characteristics. Displayed is (A) the rgb image (derived from the hyperspectral image), (B) the NDVI image and (C) the pixelwise elevation angle, calculated from depth information projected to the image coordinate system. The low NDVI values on the horizontal leaf parts are caused by the specular reflection and are not related to a lower chlorophyl concentration. Such geometric effects hamper the accurate and reliable interpretation of hyperspectral images.

Simultaneously, the sensor technology for the assessment of 3D shapes is considerably improving. Today, extremely high accurate sensor systems with high resolution are available [3] and even low cost systems reach usable levels of accuracy [4].

In consequence, combining both data types, the hyperspectral images and the 3D point clouds, to hyperspectral 3D plant models has several advantages. The explanation of various optical effects is given by the geometry. Relating both information types, the cause and the effect, in one spatial model system generated a suitable data base for describing and removing the misleading effects. Furthermore, the mapped geometric and spectral information can be used for an advanced data analysis. The combination of feature sets from both information sources or the calculation of combined features may improve the result quality for tasks like organ segmentation, detection of disease symptoms and assessment of senescence levels.

The generation of hyperspectral 3D plant models is not trivial. It requires suitable sensor techniques and computer vision methods adapted to the plant scenario. An important point is the spatial calibration of hyperspectral cameras, commonly designed as pushbroom cameras with sufficient accuracy. Common calibration routines for pushbroom cameras are not adapted to the close range and to the sensing of plants. The assessment of plant shapes requires 3D imaging techniques that handle the non-regular surface and the non-solid characteristics of the plant architecture.

On the other hand, the analysis of hyperspectral 3D models poses new challenges. The reflectance models (e.g. bidirectional reflectance distribution function (BRDF) [5, 6]) are very specific to the sensor type and the plant species. Therefore, these models have to be derived for each individual experiment with sufficient accuracy and reliability. Robust methods have to adapt the correction functions to the new experiment at best from a single hyperspectral 3D plant model. Usually, nearly all leaf angles and shading situations are included in such a model of a higher plant. Missing data need to be interpolated or derived from prior information.

The hyperspectral 3D plant models supply huge amounts of high-dimensional data that require advanced data analysis methods. The complexity of the analysis with spectral and spatial features is higher than by using a more homogenous data source. On the one hand, the different data sources partially explain each other. On the other hand, the spectral and geometric information complement each other and provide additional information. Therefore, a suitable data analysis does not simply combine the different features in a single feature vector, but uses the redundancy and complement characteristics for integrated features with more information than provided by a single sensor. Such features may support a human interpretation, but in most cases they will be optimized for a specific task, e.g. the detection of disease symptoms by a specific algorithm.

We present hyperspectral 3D plant models as an integration platform for multiple sensors and models of metabolic processes. Further, geometrically calibrated sensors may be integrated as additional texture layers. In the first part of this paper, we summarize the available sensors and methods for the generation of hyperspectral 3D plant models. In the second part, advantages and potential applications are presented.

The most important challenges for computer vision in this study are specified and highlighted. They refer to different groups within computer vision and show the diverse interesting aspects of hyperspectral 3D models.

2 Fusion of hyperspectral and shape information

In this section, common sensor systems for spectral and spatial data are introduced. Furthermore, we present an applicable and proven method for the combination of hyperspectral pushbroom cameras and 3D plant models. Combining hyperspectral measurements and geometric information is conducted by assigning the 3D coordinate of the reflecting plant surface point to the recorded spectrum. In a phenotyping context, the geometric flexibility and temporal variability of plants makes it complicated to obtain the required mapping accuracy.

2.1 Hyperspectral images

Hyperspectral cameras record the reflected radiation at narrow wavelengths with a high spatial resolution in a defined field of view. Hyperspectral imaging sensors

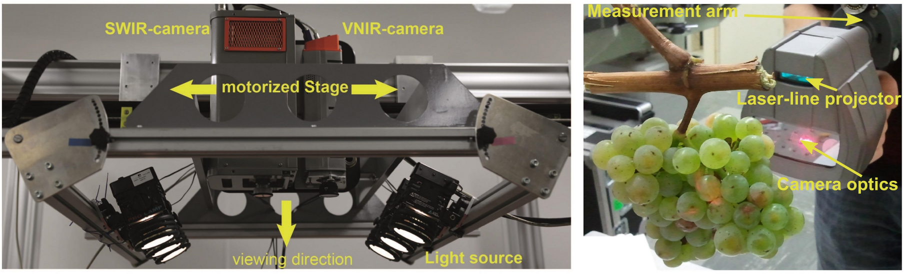

Fig. 2. The used sensors: hyperspectral sensing system including two hyperspectral pushbroom cameras and linear stage and the close range 3D laser scanner using the triangulation principle on a laser line.

which are used for plant phenotyping are based on different measurement methods. Currently hyperspectral sensors are classified depending on their spatial scale (airborne or close-range sensing), on the spectral resolution (multispectral to hyperspectral) and on the type of detector. The most common measurement principle is the pushbroom camera with a slit spreading up the incoming light of a line into its spectral composition [7]. Other principles like adapting filters are also available but less common. Interesting new developments like the Cubert UHD 185 Firefly (Cubert, Ulm, Germany) combine the advantages of line scanners and spectral filters by projecting a 2D image on a 1D slit. So far, these sensors do not reach the accuracy and resolution of pushbroom sensors.

The hyperspectral pushbroom sensor unit used in this study consists of two line scanners (ImSpector V10 and SWIR-camera, Specim, Oulu, Finland) whose viewing planes are moved across the plant (Fig. 2). The resulting hyperspectral image is represented by a data cube which is spanned by two spatial and one spectral dimension. These hyperspectral data cubes contain a spectral signature from 350 to 2500 nm in narrow wavelength for each pixel. The reflectance of plants in different ranges of the electromagnetic spectrum is driven by multiple interactions; absorption due to leaf pigments in the visible range (400 to 700 nm), scattering of light due to leaf or canopy structure in the near infrared (700 to 1000 nm) and absorption by leaf chemistry in the shortwave infrared (1000 to 2500 nm) [8]. Thus these hyperspectral imaging systems are appropriate to assess subtle differences among different plant phenotypes and the reaction of different genotypes to stress. However, the quality of hyperspectral imaging data depends strongly on the measuring setup. Hereby particularly the arrangement of the sensor to the object and the light source has to be considered.

2.2 Capturing the 3D shape of plants

Capturing the 3D geometry of plants is a common technique in plant science and can be applied across various scales like laboratory [9], greenhouse [10] and field [11]. A variety of sensors can be used to acquire the 3D geometry like stereo camera system [12], hyperspectral cameras [13], terrestrial lidar [14], laser triangulation for close-up scanning [3] or structured light approaches [15]. Close-up laserscanning using laser triangulation provides several advantages if highly accurate and resolved 3D images are necessary (Fig. 2). Smallest organs and deformations due to growth in the sub-millimeter range can be monitored on organ level with highest quality [3]. However, this technique is vulnerable to wind and the actor's movement. Scanning results are highly affected by tissue composition, surface property, size and consistence of wax layer and epidermis and the scanner set-up e.g. exposure time and angle of incidence and reflection [3]. Moreover, it is hard to track single organs when e.g. leaves change their position due to growth, the sun movement or stress.

As almost all measuring systems, laserscanning has to deal with a trade-off between measurable volume and resolution. Combinations with position-tracking-devices like lasertracker or articulated measuring arms enable an enlargement of the measurable volume to the size of some meters without loosing the advantage of resolution and accuracy [3]. Thus, laserscanning can be depicted to be method of choice for high precision 3D imaging of plants. Using laser scanned data, algorithms for automated segmentation [16] using geometry-based surface descriptors have been developed that enable an automated parameterization [17].

In this study, a Perceptron laser triangulation scanner (Perceptron Scan Works V5, Perceptron Inc., Plymouth MI, USA) was used (Fig. 2). By coupling with a measuring arm (Romer Infinite 2.0 (2.8m Version)) it provides an occlusion-free option for close-up imaging of plants and a point reproducibility of 0.088 mm. It was chosen due to its high resolution and accuracy and has been successfully applied for 3D imaging of various plants [9, 16].

2.3 Generation of hyperspectral 3D plant models

The introduced sensor types record data with differing properties. The 3D sensor records points or other geometric primitives in a 3D coordinate system and the hyperspectral imager records the reflected spectra in a 2D image reference system. The mapping and combination of spectral and geometric information requires that all data is related to a unique coordinate system.

This can be achieved by more than one approach. On the one hand, the hyperspectral camera can be calibrated in the coordinate system of the 3D plant models by corresponding points in the image and the 3D model [18]. Here arises the problem that such corresponding points are not available because the point detectors are not adapted to plant surfaces and, consequently, do not give reliable results. The transfer of algorithms and methods for man-made scenes to short-range plant scenarios is not completed and requires further impulses from the domain of computer vision.

The use of a reference object is a more promising approach. The reference object delivers automatically detectable surface points with known position in the coordinate system of the reference object and defines a unique reference coordinate system. As reference object, a composite of two horizontal, parallel planes with a chess pattern texture was used for this study. The extracted image points with corresponding 3D coordinate were used as input for the camera calibration. If the hyperspectral camera is calibrated in the reference system, the measured 3D model of the plant needs only to be transformed into the reference system. This approach turns out to deliver accurate and reliable mappings displayed in most of the figures included.

The calibration of the camera requires a calibration method and a camera model that corresponds to the measuring principle of the camera. Numerous camera calibration models are available. A pinhole camera can be described by a perspective projection matrix. A pushbroom sensor may be described by the linear pushbroom camera model of [7]. Non-linear deviations, which occur in close-range observations, can not be described by this model and have to be removed in a pre- or post-processing step.

A further challenge for the generation of hyperspectral plant models is the time factor because, in general, the spectral and geometric characteristics are not measured simultaneously. Significant inaccuracies may be caused by the non-solid architecture of the plants. When moved or even after short time in a fixed position the leaves are moving on the millimeter scale. Therefore, both measurements have to be carried out without delay and with great care and patience.

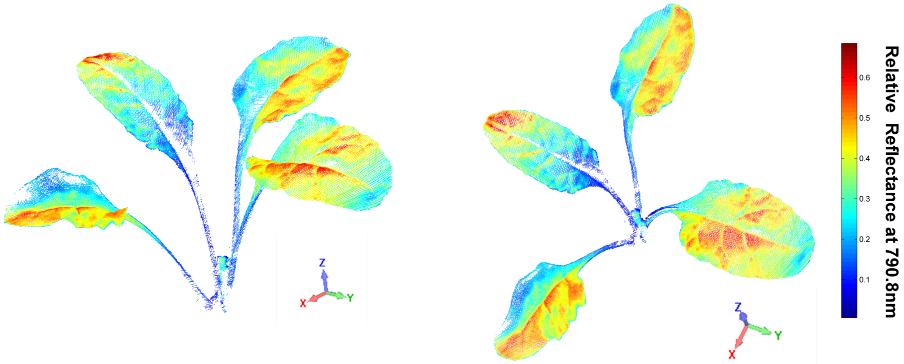

Fig. 3. 3D point cloud with a hyperspectral texture. The left part shows the oblique view and the right part a top view on the textured point cloud of a young sugar beet plant.

If the camera is calibrated, the mapping of spectral and geometric information is possible. The depth information can be projected to the image coordinate system and assigned to the single pixels (Fig. 1 (C)). Alternatively, the hyperspectral image is used as texture for the 3D plant model (Fig. 3 and Fig. 4). Such an enriched model can be termed a hyperspectral 3D plant model.

The generation of a hyperspectral texture of a 3D object is accompanied by a resampling and transformation because the pixel observations are now assigned to vertices of a meshed surface. Normally, resampling incorporates bi-linear or bi-cubic observations. At hyperspectral textures these interpolation techniques are problematic as implausible or non-biological spectra can be generated. Therefore, we used a nearest neighbor assignment and did not re-calculate new spectra.

2.4 Data set description

The supplemented data set contains the hyperspectral 3D plant model of a juvenile sugar beet plant. The sugar beet plant was observed at an age of 10 weeks by the described 3D laserscanner (section 2.2) and two hyperspectral cameras (section 2.1). The data set is designed as textured point cloud. In the supplementary material a spectrally and spatially sub-sampled version is attached. A larger version of the data set is available at *www.ikg.uni-bonn.de\datasetCVPPP*.

The data set is provided in .mat-format accessible directly via Matlab or via import routines for further analysis software. The .mat-Container contains three variables: the 3D point cloud *coord3*, the visnir texture *visnir* and the swir texture *swir*. Both textures are stored without redundancy resulting in a matrix *spectra* containing the observed spectra and a index vector *index* assigning the spectra to the points of the point cloud by $spectra\_pcl = spectra(index, :)$. A function *visualize_hyperspectral_3D_model.m*, that loads the hyperspectral 3D model and visualizes the textured point cloud, is supplied with the data set.

3 Applications of hyperspectral 3D plant models

The resulting hyperspectral 3D model constitutes a new data set with two data channels, one spectral and one spatial, that offers new and challenging applications. The combination of hyperspectral and 3D shape data is particularly suitable because these sensors are well established for phenotyping, observe different characteristics and their analysis benefits from each other. The referenced information channels regards complementary aspects and is therefore suited to reveal new traits. In general, there are two approaches to exploit the new wealth of information. On the one hand, one data channel can be used to explain and remove specific phenomena in the other data channel. On the other other hand, both data channel can be combined in a unique feature space and analyzed in an integrated way. Both approaches require innovative algorithms to exploit their full potential.

3.1 Radiometric calibration

The intensity of reflected light observed depends significantly on the plant geometry. Under the assumption of a known geometry, various effects can be removed from the observations.

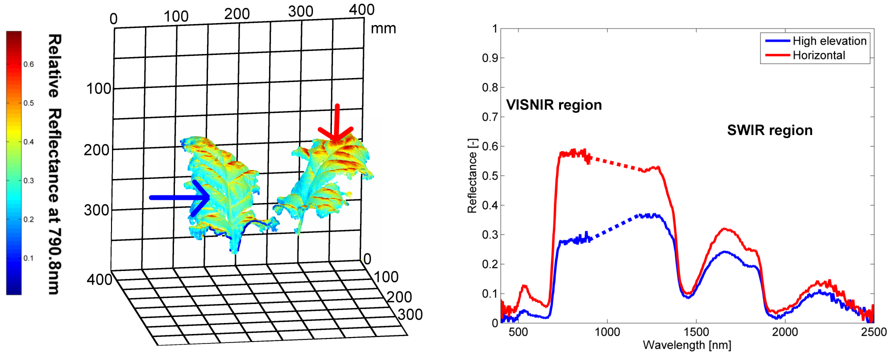

Fig. 4. Hyperspectral 3D plant model integrating the spectral information of two cameras with different spectral range and spatial resolution. In the right part, the combined spectra of the two distinct hyperspectral cameras for two points is displayed. The red spectra was reflected by a horizontal leaf part and the blue spectra from a lower leaf with a high elevation angle.

The effects of geometry on the observed spectra can be differentiated into two groups: sensor-related and plant geometry-related effects. The decreasing illumination intensity with increasing distance from the light source, the varying illumination intensity in the field of view of the camera and the varying observations angles as a result of the aperture angle of the camera are effects which depend on the sensor setup. They are static and do not depend on the specific plant geometry. However, they depend on the location of the plant where the light is reflected (x, y, z coordinate). Therefore, the modeling of sensor geometry related effects requires the information about the 3D shape of the plant.

The major part of the geometric effects are specific for the single plant geometry and related to the varying observation and illumination angles (Fig. 5). This situation is aggravated by the fact that multiple tissues of a leaf in combination with internal and specular reflection cause a complex reflection function with a "'sweet spot"' of excessive specular reflection [6]. The most important effects are elevation-dependent (angle between zenith and surface normal) reflection and self-shadowing. Both effects depend, beyond the raw coordinate, on the whole geometry of plant and sensor.

For the description of the geometry-related reflectance dependance a 6D function called bidirectional reflectance function (BRDF, [6]) is used. BRDF models are established for remote sensing applications and are proven to support the extraction of relevant parameters from hyperspectral observations [5]. However, the remote sensing BRDF models are not transferable to the close-range because, in general, they rely on a leaf angle distribution function [19]. This approach is not applicable because a sensor pixel observes a specific area on the leaf surface with an approximately constant leaf angle extractable from the 3D model. Moreover, the BRDF models depend on the plant species [6].

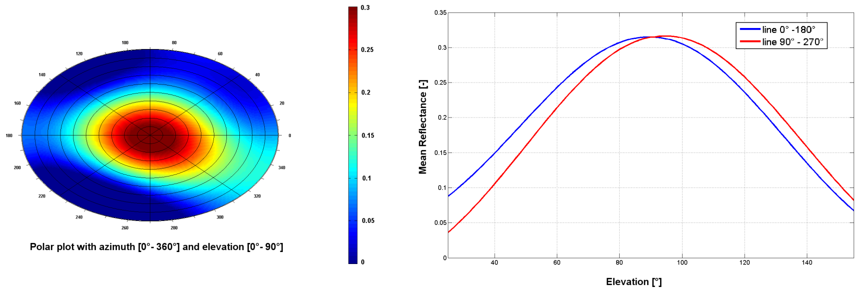

Fig. 5. Relation between the mean reflectance over all wavelength and the local elevation (angle between zenith and surface normal) extracted from a hyperspectral 3D plant model of a single leaf. The sensor setup uses 6 light spots which illuminate diffusely the plant from zenith direction.

For phenotyping purposes, the derivation of an BRDF model which is specific for each experiment, including plant species and sensor configuration, is desirable. The efficient and reliable derivation of such scenario-specific light models is an interesting task with high relevance for the computer vision community. First approaches are based on multi-angle goniometer measurements [5] and utilize predefined parametric models [19]. s

The radiometric calibration requires a light distribution model of the whole sensor system and aims at a improved image quality and an undistorted measurement of plant-physiological characteristics. This approach is common in remote sensing and is included in the process chain of satellite imaging products.

In the close range, the surface is rougher and indirect effects like self shadowing and in-leaf light transport represent a major fraction of the sensed spectral information. The complexity of the observation situation is further enhanced by multi-reflections and light transmissions through the leaves. Illuminated leaves function as light sources with distorted spectra, most probably with a peak in the green region because of absorptions by the leaf chlorophyll. High-performance simulation techniques and hyperspectral ray-tracing methods are requirements to exploit the full potential of the sensor signal [20] and at the same time for the generation of more realistic 3D plant models for virtual reality applications. Therefore, computer vision may contribute an important share to trends in plant science.

3.2 Improved classification and segmentation

The segmentation of a plant into its organs is a complex task with high relevance [3]. Plant organs are functional units with specific texture, size and position within the plant. The information about the development of single organs and the retrieval of a single organ within multiple observations is highly relevant for breeding and the quantification of disease effects. The introduced hyperspectral 3D plant models are a suitable data base for organ segmentation as two information sources are already spatially fused.

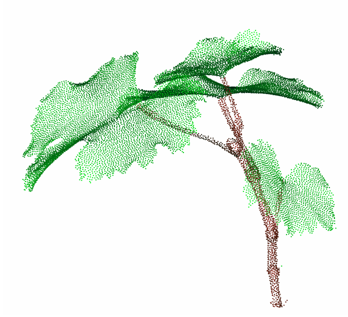

Fig. 6. Organ segmentation of a vine branch into leaves (green points) and stems (brown points) based on spatial features. Such tasks will benefit from the additional hyperspectral layer because the organs differ clearly in their reflection characteristics.

Fig. 6 shows the results of a organ segmentation of a vine branch into leaf tissue and stems.

The expected segmentation improvement will be obtained by the complementary characteristics of the two information types. This kind of fused or integrated analysis corresponds to the human way of observing. The semantic analysis of a scene by humans is based on texture information and the spatial context. Only the combined analysis of multiple information sources ensures highest reliability and recognition quality.

3.3 Spatial requests

Disease symptoms, senescence processes and growth disorders do not develop uniformly within a plant. In some cases the upper leaves and in some cases the lower leaves are more infested. Also the leaf size and age are important. Currently, hyperspectral images are analyzed with regard to the 2D image, e.g. by the ratio of infested pixels [21]. This two dimensional analysis can be extended to the third dimension by the introduced hyperspectral 3D plant models. The information at which height a symptoms appears or whether leaves of a specific size are infested more often than others is directly available and usable in an automatic way. Furthermore, the 3D model exposes the plant parts with critical geometry supporting complicated reflectance conditions for the hyperspectral images. Such image region may be excluded from further analysis.

On the other hand, the manual analysis of hyperspectral images can be extended by spatial requests and constraints. Investigations on real plants include the observation from different viewing angles. This approach is simulated by the 3D plant model as views from different direction can be simulated. Further scanerios are the fading-out of unimportant background plant parts or the focus on a specific level within the plant. This 3D-shape-sensitive visualization techniques support the explorative investigation of plant characteristics because misleading spatial proximities within the 2D image caused by overlapping leaves and the projection in the image plane are neglected.

3.4 Hyperspectral 3D plant models as an integration platform

Current phenotyping platforms integrate multiple sensors. These sensors record multiple plant characteristics, each within a distinct reference system and scale. Pointwise measurements are conducted by some chlorophyll fluorescence sensors, gas-based measurements of the metabolism regard the whole plant, pinhole cameras perform a perspective projection of the plants' reflectance characteristics and hyperspectral pushbroom cameras record the reflected light intensities line by line. The 3D shape sensors can be based on multiple measurement principles and determines the point location in its local coordinate system.

So far, the data of all these sensors is recorded, stored and analyzed separately and the results are combined as a description of a plant. This approach is very simple and reliable, as a data integration is not necessary and a sensor failure does not affect the other measurements. However, the recorded signals are not independent but they are caused partly by the same characteristic and can be used to explain partly the observed phenomena. A separate analysis neglects these relations and does not reach the optimal analysis result which can be achieved by an integrated analysis.

Therefore, we propose to use the 3D model of the plant as an integration platform for all measurements conducted at one plant. For this purpose, all sensors have to be defined and calibrated in a unique coordinate system (Fig.4). The measurements are assigned to the surface part which has been observed and stored with the additional spatial context. This additional effort of calibration and referencing provides directly referenced measurements of all sensors in a unique coordinate system. As in a example, destructive measurements of pigment concentrations at specific leaf points can be stored with relation to the plants' coordinate system. Further developments may enable a growing coordinate systems, the phyto-reference-system, which allows to track symptoms and specific phenomena over time by relating the 3D models of different observation days to each other.

Such plant model can be further enriched by process models to build a functional - structural plant model (FSPM) with additional real measurements [22]. Simulation of nutrient fluxes can be used to predict the development depending on environmental factors. The comparison of simulated and observed plant development will help to improve the growth models and extend the knowledge about the development mechanisms of plants.

The visualization of the generation, degradation and transport of substances within the plant is an interesting field for computer graphic. Particularly the different scales, from single cells to plant or field scale in a unique model, demand both generalizing and specific visualization techniques.

4 Conclusion

We present hyperspectral 3D plant models as a solution approach for the misleading geometric effects which prevent an accurate hyperspectral imaging. On the other hand, the referenced data channels induce a number of open questions in generation as well as in analysis. The majority of these open tasks can be assigned to the field of computer vision. From the perspective of the computer vision community the combination of hyperspectral and geometric data can be a connecting point to the plant research. Different groups can work on subproblems.

We have identified several tasks for computer vision in the context of hyperspectral 3D models. The generation of hyperspectral 3D models demands for feature descriptor adapted to plant surfaces in 2D images and 3D point clouds. The generated hyperspectral 3D plant models require analysis methods that regard the specific relations between the two data channels. Especially, the high dimensional hyperspectral data contains high levels of redundancy which impairs the results quality. So far, the geometry-based radiometric calibration of hyperspectral plant images is neglected in the close-range. To improve the quality of high dimensional plant phenotyping data the measurement specifications have to be considered in detail, since i.e. spectral signals of plants are influenced by geometric configuration of sensor and illumination and the plant geometry. A combination of hyperspectral imaging with 3D laserscanning allows to model and to remove these effects from the data. It requires hyperspectral, virtual simulation environments integrating hyperspectral raytracing algorithms adapted to plant tissues. Methods for measuring and parameterizing the reflection characteristics of plants are required.

We believe that hyperspectral 3D plant models can improve the phenotyping results and that they are a chance for the computer vision community to face real world problems. We are convinced that the computer vision community can contribute to the solution for the grand challenges facing society. The accelerated breeding and improved precision crop protection substantially contributes to safeguard the food supply while reducing the used resources such as water, fertilizer and pesticides.

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