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Detection of early plant stress responses in hyperspectral images

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ABSTRACT

Early stress detection in crop plants is highly relevant, but hard to achieve. We hypothesize that close range hyperspectral imaging is able to uncover stress related processes non-destructively in the early stages which are invisible to the human eye. We propose an approach which combines unsupervised and supervised methods in order to identify several stages of progressive stress development from series of hyperspectral images. Stress of an entire plant is detected by stress response levels at pixel scale. The focus is on drought stress in barley (*Hordeum vulgare*). Unsupervised learning is used to separate hyperspectral signatures into clusters related to different stages of stress response and progressive senescence. Whereas all such signatures may be found in both, well watered and drought stressed plants, their respective distributions differ. Ordinal classification with Support Vector Machines (SVM) is used to quantify and visualize the distribution of progressive stages of senescence and to separate well watered from drought stressed plants. For each senescence stage a distinctive set of most relevant Vegetation Indices (VIs) is identified. The method has been applied on two experiments involving potted barley plants under well watered and drought stress conditions in a greenhouse. Drought stress is detected up to ten days earlier than using NDVI. Furthermore, it is shown that some VIs have overall relevance, while others are specific to particular senescence stages. The transferability of the method to the field is illustrated by an experiment on maize (*Zea mays*).

1. Introduction

Crop yield is subject to the environment and its variable growing conditions. Deviations of biotic (e.g. diseases or insects) or abiotic (e.g. drought or out-of-range temperatures) environmental factors which exceed a critical level act as stressors and induce plant stress (Gaspar et al., 2002; Taiz and Zeiger, 2010). Under prolonged stress, crop growth and productivity are impaired (Gaspar et al., 2002). For the United States, it has been estimated that major crops achieve only 22% of their genetic potential yield due to suboptimal growing conditions (Boyer, 1982; Taiz and Zeiger, 2010). Minimizing this gap by a better exploitation of the genetic potentials of crops is becoming more and more important: an increasing world population and the substitution of fossil fuels by crop products require an increase in agricultural output of 70% by 2050 (FAO, 2009), an order of magnitude which has never been reached in the past. Moreover, growing conditions will be affected by ongoing climate change (e.g. Reynolds, 2010; Gornall et al., 2010). Agricultural science is challenged to meet the demand for enhanced crop productivity by improving methods of crop management (Davies et al., 2011) and by breeding crops with higher stress tolerance levels (Tester and Langridge, 2010). Breeding and crop management will benefit from a deeper understanding of the processes that a plant initiates in the early stages of stress reaction. Therefore, it is important to identify, quantify and visualize stress responses in the early stages – before irreversible damages and yield loss occur (e.g. Chaerle and Van Der Straeten, 2000; Lichtenthaler et al., 1996; Römer et al., 2012).

In this paper, we focus on the detection of early *drought* stress, which is not yet visible to the naked eye. Drought stress, induced by water shortage, is one of the biggest challenges in global crop production (Pennisi, 2008; Tuberosa and Salvi, 2006). It occurs, if a plant's transpiration rate exceeds its water uptake and is closely linked to the basic processes of absorption of light energy and the production of biomass through photosynthesis (Taiz and Zeiger, 2010). This process requires that the plant assimilates carbon from the atmosphere. The assimilation is regulated by the aperture of stomata, which are microscopic pores in the epidermis. Opening of stomata, however, is responsible for significant loss of water via transpiration (Taiz and Zeiger, 2010). Hence, transpiration and photosynthesis are inseparably linked and a plant's need for

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carbon uptake can only be satisfied at risk of water loss. Thus, increasing yield under drought conditions is a complex optimization problem for breeders and management, which is termed "more crop per drop" (e.g. FAO, 2003 or Marris, 2008).

If water shortage exceeds a critical level, a plant initiates stress responses which result in biochemical and morphological adaptations. An important response process, in which resources are reallocated within the plant, is leaf senescence. Basically, leaf senescence denotes the final phase of leaf development. Under drought stress, it may be induced prematurely (Lim and Nam, 2007). Leaf senescence is a spatiotemporal process, which is actively regulated by hormones, and which allows the plant to attain the reproductive state under drought conditions. The process is characterized by a degradation of pigments and the relocation of nutrients. Leaf senescence develops in patterns which proceed from older to younger leaves and, within a leaf, from the tip towards the leaf base (Guiboileau et al., 2010; Lim and Nam, 2007). It is a continuous process that is invisible to the naked eye in its early stages. If wilting leaves are observable, irreversible damage to plant and yield occur. Early senescence stages have been investigated by the use of invasive biochemical analysis (e.g. Fischer, 2012).

The challenge of observing the early stages of this process non-invasively can be met by using hyperspectral sensors, which detect senescent changes in the spectral reflectance characteristics of leaves. These changes are mainly related to the aforementioned degradation of pigments (particularly chlorophyll), which alters the ratios between reflected, absorbed and transmitted radiation (Blackburn, 2007). For biotic stress, it has been demonstrated that the use of hyperspectral data facilitates a presymptomatic identification of plant diseases (Rumpf et al., 2010).

In contrast to most plant diseases, drought stress does not manifest itself in local symptoms. The reallocation of resources involves the entire plant – and occurs in all plants to a specific degree, even in the well-watered ones. Drought stressed plants are characterized by early and accelerated leaf senescence (Munné-Bosch and Alegre, 2004). The detection of this creeping process and distinguishing it from normal variations requires spectral information with high degrees of temporal and spatial resolution.

We hypothesize that series of hyperspectral images provide information which allows a description and detection of drought stress processes before changes occur which are visible to the naked eye. Hyperspectral imagers permit the capturing of spatiotemporal processes within entire plants and facilitate the observation of the spatial distribution of senescence – even within single leaves (Fig. 1). In contrast to biochemical analysis, their non-invasive characteristics enable the monitoring of stress related processes without affecting them.

Detection of early stress responses based on hyperspectral images is complicated by the following difficulties:

- The signal to noise ratio is bad. Spectral observations are affected by sensor noise and factors like shadowing and leaf inclination.
- Stress related processes are not well differentiated from normal deviations.
- Both, spatial and spectral redundancy have to be taken into account.
- Since the focus is on processes which are invisible in the early states, label information is not available at the pixel scale. It is, however, available at the plant (pot) scale.

The contribution of this paper is a method for the early detection of drought stress in time series of hyperspectral images. As the senescence process occurs in all plants, the differentiation between the treatments is based on different distributions, i.e. histograms, of plants' vitality. These histograms are derived from the frequencies of the senescence classes at pixel scale. In order to derive these senescence classes we propose an approach which comprises:

- combining an unsupervised method (*k*-Means clustering) for extracting labels at pixel scale and a supervised method for classification (Support Vector Machines), on both scales, pixel and plant,
- providing an ordinal classification method for a discrete representation of progressive senescence,
- selecting specific feature sets for each level of senescence using a wrapper approach.

The applicability of the proposed method is demonstrated on series of hyperspectral images from two drought stress experiments with single barley plants (*Hordeum vulgare*). The result is a description of the senescence state of each plant. We use the relative frequencies of the senescence classes within an image as features for an early detection of drought stress. Furthermore, we present a visualization of the spatiotemporal senescence distribution which covers also early and invisible states of senescence. It will be shown that our approach is superior to a single VI. We will also demonstrate the transferability of the method to the field

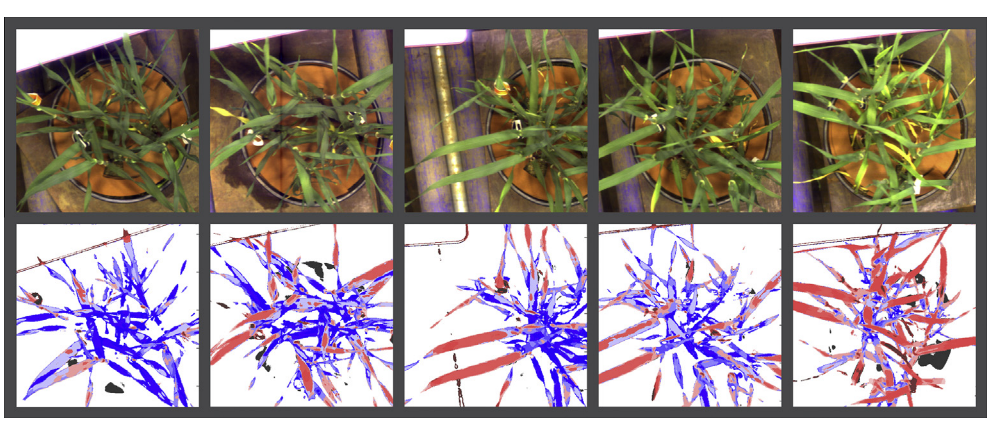

Fig. 1. Time series of a drought stressed barley plant (snapshots from Fig. 11). Hyperspectral images were taken on alternate days from day 2 to day 10 after the initiation of drought. The upper row shows RGB images, the lower false color images of predicted labels. The colors from blue to red indicate the range – from unstressed areas with high chlorophyll content to severe stress. White color represents removed background pixels.