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Pixel classification methods for identifying and quantifying leaf surface injury from digital images

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ABSTRACT

Plants exposed to stress due to pollution, disease or nutrient deficiency often develop visible symptoms on leaves such as spots, colour changes and necrotic regions. Early symptom detection is important for precision agriculture, environmental monitoring using bio-indicators and quality assessment of leafy vegetables. Leaf injury is usually assessed by visual inspection, which is labour-intensive and to a considerable extent subjective. In this study, methods for classifying individual pixels as healthy or injured from images of clover leaves exposed to the air pollutant ozone were tested and compared. RGB images of the leaves were acquired under controlled conditions in a laboratory using a standard digital SLR camera. Different feature vectors were extracted from the images by including different colour and texture (spatial) information. Four approaches to classification were evaluated: (1) Fit to a Pattern Multivariate Image Analysis (FPM) combined with T^2 statistics (FPM-T^2) or (2) Residual Sum of Squares statistics (FPM-RSS), (3) linear discriminant analysis (LDA) and (4) *K*-means clustering. The predicted leaf pixel classifications were trained from and compared to manually segmented images to evaluate classification performance. The LDA classifier outperformed the three other approaches in pixel identification with significantly higher accuracy, precision, true positive rate and F-score and significantly lower false positive rate and computation time. A feature vector of single pixel colour channel intensities was sufficient for capturing the information relevant for pixel identification. Including neighbourhood pixel information in the feature vector did not improve performance, but significantly increased the computation time. The LDA classifier was robust with 95% mean accuracy, 83% mean true positive rate and 2% mean false positive rate, indicating that it has potential for real-time applications.

1. Introduction

Plants are exposed to a wide variety of stresses including disease, nutrient deficiency, drought and pollution which can affect growth, the diversity of natural vegetation and crop production. These stresses often give rise to visual symptoms on the leaf surfaces such as spots, streaks, colour changes and necrotic regions. Visible lesions may initially be difficult to distinguish from healthy leaf regions and may change in colour, shape and size as the lesion develops. Leaf injury, regardless of the cause, is usually assessed by visual inspection. This procedure relies on human experts and is time-consuming, labour-intensive and to some extent inconsistent (Bock et al., 2010). Digital image analysis has the potential for providing rapid, consistent and non-destructive leaf inspection at reasonable costs. Such systems can be used in crop management for targeted application of fungicides/pesticides/herbicides or fertilizers, quality inspection of leafy agricultural products or environmental monitoring using bio-indicators.

Ground-level ozone pollution is a global air pollution problem resulting in reduced crop yield and quality. Global crop production losses due to ozone pollution for the year 2000 are estimated to be US$11-18 billion (Avnery et al., 2011a) and are projected to reach up to US$35 billion by 2030 (Avnery et al., 2011b). Ozone exposure often results in visible leaf injuries characterized by chlorotic and necrotic spots or regions across the leaf surface and subsequent leaf senescence and abscission (Wilkinson et al., 2012). Clover

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(*Trifolium*), an important pasture crop, readily develops visible symptoms and has been used as an ozone bio-indicator and to develop critical levels for plant ozone effects within the UN-ECE Convention on Long-Range Transboundary Air Pollution (Karlsson et al., 2003, 2009).

Several studies have explored methods based on image processing for classifying whole leaves into categories for purposes such as plant species identification (Cope et al., 2012; Gwo et al., 2013), crop and weed discrimination (Ahmed et al., 2012; Arribas et al., 2011), determination of healthy and diseased plants (Pydipati et al., 2006; Xu et al., 2011) as well as leaf quality grading for the consumer market (Lunadei et al., 2012; Zhang and Zhang, 2011). These studies do not, however, consider classification of individual leaf pixels. Identifying leaf pixels or regions that deviate from normal leaf pixels could reveal disease or injury at an early stage, characterize the severity or stage of the leaf lesion and enable diagnosis of the lesion according to disease type.

A common approach to leaf region/pixel classification is often to segment the region of interest, extract relevant features from the selected region and use these features for region classification by some classifier. Huang (2007) developed a classification system to identify leaf lesions from three different orchid diseases. Infected leaf areas were first segmented from the background using an exponential transformation and standard image processing techniques. Texture features derived from the grey level co-occurrence matrix (GLCM) and colour features were used to classify these extracted areas using a back-propagation neural network classifier. Camargo and Smith (2009a) used a segmentation procedure based on the distribution of the intensity histogram of colour transformed leaf images followed by post-processing using morphological operations to remove pixel regions not considered part of the region of interest. The procedure performed well in some cases with around 90% identified diseased pixels, but poorly in other cases with around 50–60% identified diseased pixels. Once the diseased region was identified, texture-related features of the region were used as discriminators for support vector machine classification of the type of disease (Camargo and Smith, 2009b). Zhang and Meng (2011) used a boosting algorithm to select significant features for segmenting the leaf lesion from the background followed by extraction of zone-based local texture features for classification of the lesion type and obtained classification rates similar to human experts.

Another more direct approach is to classify leaf pixels directly without the use of segmentation. Boese et al. (2008) used an unsupervised algorithm to group leaf pixels with similar RGB values into a user given number of classes. These classes were then defined by the user as healthy, diseased or injured leaf areas. Accuracy, precision, recall and computation time of the method were not reported. Sanyal and Patel (2008) used a feature vector that combined colour and 7×7 pixel neighbourhood information extracted from leaf images and a multilayer perceptron classifier to detect two different diseases on rice leaf surfaces. Although an overall pixel classification accuracy of 89% was stated, the precision, recall and computation time of the method were not discussed. Bauer et al. (2011) tested two pixelwise methods, *k*-nearest neighbour and a Gaussian mixture (GM) model, and one global probabilistic model (conditional random field (CRF) model) for classifying diseased leaf pixels from stereo images of sugar beet leaves infected with two types of fungi. Although the kNN classifier used long computation time and did not achieve the desired classification rate levels, the GM and the CRF models were promising, with the GM model giving classification rates in the range 86–94%. The best classification rates were obtained when using a feature vector that included colour as well as 4-connected neighbour pixel information. Other neighbourhood relations were not tested. Both GM and CRF models, however, require finding appropriate model parameters, such as the weighting functions and number of and parameters of Gaussian distributions for GM models and parameters of the energy function for CRF models which may be difficult to solve for exactly (Bauer et al., 2011).

In this study, we test and compare four approaches for classifying individual leaf pixels directly as healthy or injured from clover leaf RGB images with different degrees of ozone-induced visible injuries. The aim was to determine which combination of feature vector and classifier provided the superior all-round classification performance. Different feature vectors were derived from the images by including different colour and texture information. Three colour spaces, (1) the original RGB colour space, (2) the CIE 1976 $L^*a^*b^*$ colour space (McLaren, 1976) and (3) the CIE 1976 uniform chromaticity scale diagram (UCS) (CIE, 1986), were compared to determine which colour space was best suited to capture leaf injury. Texture characteristics were included by considering two-dimensional square windows of different sizes of neighbour pixel intensity values for each pixel (Bharati et al., 2004; Prats-Montalbán et al., 2011).

Four classification approaches were compared in this study: (1) Fit to a Pattern Multivariate Image Analysis (FPM) combined with T^2 statistics (FPM-T^2), (2) Fit to a Pattern Multivariate Image Analysis (FPM) combined with Residual Sum of Squares statistics (FPM-RSS) (Prats-Montalbán, 2005), (3) linear discriminant analysis (LDA) (Fisher, 1936) and (4) the commonly used *K*-means clustering (Jain, 2010). The Fit to a Pattern MIA approach was chosen as it is a general approach for defect detection in random colour textures (Prats-Montalbán, 2005) and has been used successfully in several applications such as identifying diseased areas on citrus fruits (Lopez-Garcia et al., 2010), detecting defects on ceramic tiles and high quality stone surfaces (López et al., 2006; Prats-Montalbán and Ferrer, 2007) as well as in metallurgic problems (Bharati et al., 2004). It was chosen as leaf ozone lesions can be regarded as defects on a leaf surface. The LDA and *K*-means techniques (Michie et al., 1994; Ripley, 1996) are standard and robust classification methods, applicable also to large datasets, as in the present study, where the training set consisted of several million pixels and the test set of several hundred thousand pixels to be classified. The LDA and *K*-means methods were therefore chosen instead of, for example, a multilayer perceptron classifier as used by Sanyal and Patel (2008) for leaf pixel classification, which due to the nonlinear dependence of the cost function on the unknown parameters, can converge slowly and nonsmoothly. In addition, the LDA and *K*-means techniques do not require considerable heuristic parameter tuning, as do other classifiers such as Gaussian mixture, multilayer perceptron or conditional random field models. The resulting leaf pixel classifications were compared to manually segmented images representing the ground-truth to evaluate classification performance.

2. Materials and methods

2.1. The image datasets

The leaf images originated from studies of leaf injuries induced by ozone in the ozone sensitive species subterranean clover (*Trifolium subterraneum* L.), (see Vollsnes et al., 2009 for experimental details). *T. subterraneum* L. (Svalöf Weibull AB, Svalöf, Sweden) seeds were germinated in trays containing sandy peat soil and transplanted individually into pots containing sandy peat soil after fourteen days. The plants were kept in an environmentally controlled growth room at 20 ± 1 °C, >60% relative humidity and with a 16 h light/8 h dark cycle. Ozone treatment started when the plants were 31 days old and was applied for six hours during midday (10:00–16:00) for three consecutive days. During ozone treatment, plants were positioned randomly in six Perspex ozone