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Green plant segmentation in hyperspectral images using SVM and hyper-hue

Huajian Liu, Brooke Bruning, Bettina Berger, Trevor Garnett

Australian Plant Phenomics Facility, The Plant Accelerator®, School of Agriculture, Food and Wine
University of Adelaide, Waite Campus
Building 32, Hartley Grove, Urrbrae, SA 5064
Corresponding author's Email: huajian.liu@adelaide.edu.au

Abstract

Green plant segmentation plays an import role in hyperspectral-based plant phenotyping, however, this topic is not given enough consideration. Existing image segmentation methods are dependent on data types, plants and backgrounds and might not utilise the power of hyperspectral data. We proposed a one-class support vector machine classifier combined with a pre-processing method named hyper-hue to segment green plant pixels in hyperspectral images. Experimental results showed that his method can segment green plants from backgrounds with fewer errors and therefore could be used as a general method for hyperspectral-based green plant segmentation.

Keywords: Hyperspectral image processing, Image segmentation, Plant phenotyping

1 Introduction

Hyperspectral imaging is a widely accepted and fast developing technology for plant phenotyping [1]. For most hyperspectral image analysis tasks, green plant segmentation is a necessary prerequisite which plays an import role for subsequent image processing procedures, however, the significance of this task is not well documented in current literature.

In the visible and near-infrared (VNIR) spectra, some vegetation indices developed for multispectral images, such as hue and normalized difference vegetation index (NDVI) [2], have been used, however, these indices did not take the advantages of the power of hyperspectral data for more accurate processing. In the range of short wavelength infrared (SWIR), the segmentation methods are application-dependent and there are no well-accepted procedures for reliable segmentation.

After an investigation of the most often used vegetation indices, hyperspectral image pre-processing methods and classifiers, this paper proposes an image segmentation method which uses the combination of hyper-hue [3] and one-class support vector machine (SVM) to segment green plants from the background in hyperspectral images. The method was tested using five different plant species in both VNIR and SWIR data and the experimental results showed that it can significantly reduce errors and could be adopted as a general approach for green plant segmentation in hyperspectral images.

2 Material and methods

Five plant species, including wheat (*Triticum aestivum*), barley (*Hordeum vulgare*), cotton (*Gossypium spp.*), arrowleaf clover (*Trifolium vesiculosum*) and Australian canary grass (*Phalaris aquatic*) were grown at The Plant Accelerator® (Australian Plant Phenomics Facility, University of Adelaide, Adelaide, Australia) in 2018. Each species has 70 to 200 pots. When the plants had enough leaves, the hyperspectral images were captured with a high-throughput WIWAM hyperspectral imaging system (WIWAM, Eeklo, Belgium). Two cameras were used to capture both of VNIR and SWIR images simultaneously in the dark chamber of the WIWAM system. The FX10 camera (Specim, Oulu, Finland) captured the VNIR data from 400 nm to 1000 nm with 1.3 nm bandwidth and the SWIR camera (Specim, Oulu, Finland) acquired data in the range of 1000 nm to 2600 nm with 5.7 nm bandwidth.

A classifier was trained and validated using a part of the data of wheat and then was tested using the independent data of the five plant species. In our initial study, after testing the well-accepted classifiers and pre-processing methods of hyperspectral data, we found that the supervised one-class SVM and hyper-hue outperform others. In VNIR or SWIR data, a one-class SVM was trained, validated and tested using the following steps. (1) The hyperspectral images were calibrated using Eq. (1),

$$r_{\mathrm{p}}(\lambda, x, y) = \frac{i_{\mathrm{p}}(\lambda, x, y) - i_{\mathrm{d}}(\lambda, x, y)}{\mathrm{i}_{\mathrm{w}}(\lambda, x, y) - i_{\mathrm{d}}(\lambda, x, y)} \quad (1)$$

where r_{p} is the reflectance values of the plant at the spatial location (x, y) and the wavelength λ. i_{p}, i_{d} and i_{w} represent the measured intensity values of plants, dark references and white references respectively. (2) The noisy bands with the wavelengths below 450 nm in the VNIR data and above 2400 nm in the SWIR data were removed. (3) 5000 pixels were selected manually and randomly from the top, middle and bottom parts of the wheat leaves in the 199 hyperspectral images of wheat, excluding the pixels on the borders of the leaves whose spectral signatures were the mixture of the leaves and backgrounds. Similarly, 2500 pixels of backgrounds were collected, including pots, bolt, soil, plastic, random noise, etc. 2500 pixels were randomly selected from the 5000 pixels of wheat as training data and the remaining 2500 pixels plus the 2500 pixels of backgrounds were used as validation data. (4) The data was transformed from the original space of hypercube to the space of hyper-hue [3] whose performance for material classification has previously been proven [4, 5]. (5) A one-class classifier of SVM with the radial basis function (RBF) kernel (python sklearn toolbox, svm.OneClassSVM) was trained and validated using the training and validation data. The parameters were tuned to get the optimized performance. The trained model is named HH in this paper. (6) The trained model was tested in hyperspectral images of different plant species which were independent of the training and validation data.

3 Experimental results and discussion

To evaluate the contribution of hyper-hue in step (4), another model which used similar training processes while ignoring step (4) was trained and the model is named REF in this paper. At first, the models were validated using the validation data and the errors are listed in Table 1, in which FP, FN and MIS represent false positive rate, false negative rate and misclassification rate respectively. Table 1 shows that, compared with the REF method, the HH method can reduce the errors to the levels of lower orders. As explained by Liu, et al. [3], hyper-hue is independent of saturation and intensity and therefore it is less affected by unstable illumination from the angular deviation of local surfaces and self-shadows of plants. Also, hyper-hue could increase inter-class distance [4]. Next, the models were tested using hyperspectral images of wheat, barley, cotton, arrowleaf clover and Australian canary grass. For each species, a hyperspectral image which was independent of the training and validation data was randomly selected for testing. The images were firstly manually segmented using the Photoshop software and then were compared with the automatic segmentation. In the VNIR data, we compared several well-accepted vegetation indices, including NDVI, green normalized difference vegetative index (GNDVI), enhanced vegetation index (EVI) [6], etc. and found that the method using EVI with the threshold 0.3 can provide the best segmentation. The performances of the EVI, REF and HH methods were tested in the VNIR data while only the REF and HH methods were tested in the SWIR data. The misclassification rates are plotted in Figure 1 and Figure 2 and they show that the HH method significantly reduced the errors. Figure 3 shows the testing images of the REF and HH methods for the segmentation of barley in SWIR data.

Table 1 Error rates of SVM model validation

	VNIR			SWIR		
	FP	FN	MIS	FP	FN	MIS
REF	10.00%	0.32%	3.98%	0.20%	0.16%	0.18%
HH	0.00%	0.02%	0.02%	0.00%	0.04%	0.02%

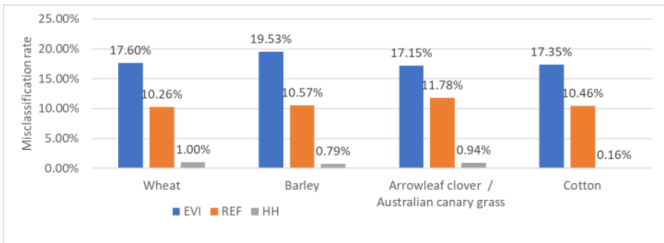


Figure 1 Misclassification rate in VNIR testing data

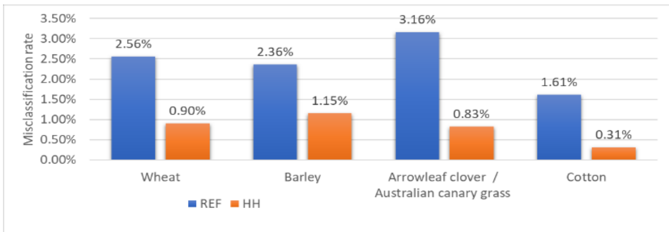
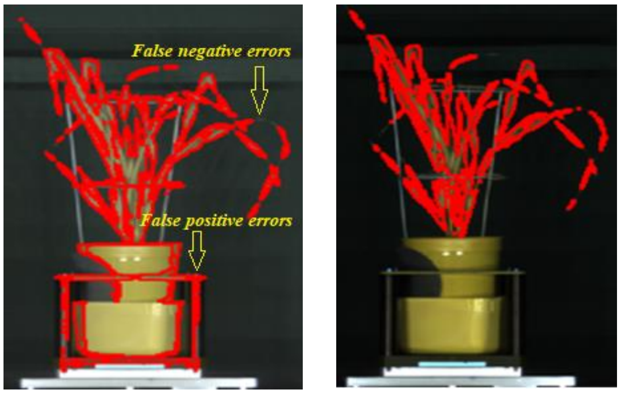


Figure 2 Misclassification rate in SWIR testing data

In the testing data, the error rates are higher than that in the validation data. There are several factors which could cause a higher error rate in the testing data. First, in the manual segmentation, the pixels on the borders of the leaves were classified as foreground while in automatic classification, these pixels could be classified as background since the spectral signatures of these pixels were the mixture of backgrounds and plants. Second, the manual segmentation could have errors, especially for the narrow-leaf plants of wheat and barley. The segmented images will be further processed to analysis the nutritional distribution in the plants, including nitrogen, phosphorous, etc. The accuracy of the segmentation can meet this requirement. Use larger training data to train more complex models, such artificial neural network (ANN) or deep-ANN, would obtain the same or better result, however, using a smaller data set to train a model with acceptable accuracy is preferred when labour and cost of data collection is concerned.



REF method HH method

Figure 3 Testing images of the REF and HH method for the segmentation of barley in SWIR data (the red colour marks the contours of the plants)

4 Conclusion

Green plant segmentation in hyperspectral images is important for plant phenotyping. This paper introduces a segmentation method which uses the combination of SVM and hyper-hue[1]. Experimental results showed that this method outperformed the approaches using vegetation indices or SVM only. The model was trained using the data of wheat and worked equally well for other species. The modelling method was suitable for both VNIR and SWIR data. In the future, this green plant segmentation method will be further tested using data collected in the field, such as on aircrafts or ground-based vehicles.

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