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Remote Sensing of Weeds in Field Crops via Image Processing: A Short Literature Collection

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Abstract

This short technical report briefly examines and discusses some of the major literature relevant to remote sensing of weeds in row crops using remotely-collected images. The basic problem is introduced, following by short discussions of remote crop sensing using UAVs and other methods, collected image processing, and vegetation classification methods. This report provides a basic collection of high-impact work in this area which may act as a starting place for a formal review of crop/weed detection methods.

Keywords: Remote sensing; image processing, weed detection

Software and Code: No code or software was used in the completion of this technical report

1 Introduction

In modern agriculture, herbicide application provides the most effective and time-efficient method of managing weeds [1]. Typically, herbicides are applied by broadcast spraying to cover a large area [2]; however, this not only requires vast quantities of herbicides and wasted water but can be harmful to the environment, particularly to local ecosystems near the crop fields. Herbicides can have adverse effects on biotic and abiotic environments and risk harming human health as well [3–5]. The long term impacts of herbicide residues, especially after repeat applications, are less well understood but is unlikely be positive. Therefore, reducing the amount of herbicide used in modern agriculture is an important step in achieving sustainable and efficient agriculture. In order to increase productivity while reducing the amount of harmful chemicals used and water wasted (both for weed control and for fertilization), the concept of precision agriculture was introduced [6–8]; this can be used to allocate the appropriate herbicide dose at exactly the right time and place [9]. While a promising technology, accurate identification of the weeds, separated from the crops, within a farm field remains a major challenge for the effective and widespread application of this work.

This short report provides a collection of the major literature in this area to act as a starting place for a formal review or article-appropriate review of the literature. This is not a formal, structured review and is to be used as a helpful tool to aid in the study of weed detection via remote sensing. It is also a good starting place for students or non-experts in the field to begin learning about the topic via the highest-impact and most respected literature in the field. Analysis of the filed and conclusions/future research directions are left to the reader and will not be presented in this report.

2 Remote Sensing

Several major studies have been done to explore methods for remotely, quickly, and accurately detecting plants using a diversity of methods [10–14]. The use of unmanned aerial vehicles (UAVs) has become a widely popular method for monitoring farmland [15–17], as they are reliable, cheap, and have a very small impact on the local environment. Compared with ground vehicles, they can cover large areas in a short time and capture high-quality images of the crops for later analysis [18]. While tracking of the crops is well-developed and easy, equivalently good tracking of weeds has proven to be a difficult problem, especially within tall and leafy crops such soybeans.

3 Collected Image Segmentation and Processing

The methods thus far developed for this generally involve the segmentation of vegetation images to locate weeds by finding areas of vegetation that are different than the main crop or that are clearly in the wrong location. Significant work on vegetation segmentation using RGB and multi-spectral images has been undertaken, focusing on the use of UAV-collected images of common crops. Hamuda et al. [19] collected information about various techniques for image segmentation and presented them in the form of a review; the methods discussed mostly involved using threshold-based methods and learning-based segmentation methods. Some of the major recent threshold methods relevant to weed detection discussed were those by Tellaeche et al. [20], Kirk et al. [21], and Jeon et al. [22], as well as classic methods such as those by Otsu [23], Marchant et al. [24], and Reid & Searcy [25]. Learning methods were also discussed, especially focused on 24-bit RGB methods (for color images) [26–29] but there was also discussion of other methods such as hue-intensity [30], LUV space [31], and lab color space [32, 33]. A recent major work in this area included a study by Torres Sanchez et al. [34] which investigated an automatic thesholding method based on the Normalized Difference Vegetation Index (NDVI) and Excess Green (ExG) Index [35] to detect vegetation. This approach was able to separate vegetation from various background with a success rate of over 90%.

4 Vegetation Classification

Classification of the vegetation after identification is another major challenge, as it is necessary to distinguish weeds from good crops for a weed detection method to be valuable. Pena et al. [36] developed a method using multispectral imagery to map weeds in maize fields; this technique used super-pixels divided according to the spacial and spectral characteristics of the images, effectively tracing crop lines and vegetation segmentation. Discrimination of the weeds was done by calculating the deviation of the observed plants with the mapped crop lines. Another method is to use a Hough transform, as discussed in studies by Tellaeche et al. [20], Gee et al. [37], Montalvo et al. [38], Bakker et al. [39], and Bah et al. [9]. The study by Bah et al. used a combination of super-pixels and a Hough transform for weed discrimination, where 400 square-pixel images of corn and beet field were used to test the method. The detection rate was 90-94% using the method, but the algorithm seemed to have a more difficult time detecting weeds in the more leafy beet plants, as the corn plants are more narrow and easier to locate in straight rows. The corn images produced excellent results, with a detection rate near 100% for low, moderate, and high infestation rates; the leafy beet plants showed good results for low infestation rates, but does not appear to have been tested for medium and high infestation rates.

References

[1] J. H. Westwood, R. Charudattan, S. O. Duke, S. A. Fennimore, P. Marrone, D. C. Slaughter, C. Swanton, and R. Zollinger, "Weed management in 2050: Perspectives on the future of weed science," *Weed Science*, vol. 66, no. 3, pp. 275–285, 2018.

[2] T. R. Legleiter, B. G. Young, and W. G. Johnson, "Glyphosate plus 2, 4-d deposition, absorption, and efficacy on glyphosate-resistant weed species as influenced by broadcast spray nozzle," *Weed Technology*, vol. 32, no. 2, pp. 141–149, 2017.

[3] L. Horrigan, R. S. Lawrence, and P. Walker, "How sustainable agriculture can address the environmental and human health harms of industrial agriculture.," *Environmental Health Perspectives*, vol. 110, no. 5, pp. 445–456, 2002.

[4] A. V. Bruggen, M. He, K. Shin, V. Mai, K. Jeong, M. Finckh, and J. Morris, "Environmental and health effects of the herbicide glyphosate," *Science of The Total Environment*, vol. 616-617, pp. 255–268, 2018.

[5] J. Sandström, A. Broyer, D. Zoia, C. Schilt, C. Greggio, M. Fournier, K. Do, and F. Monnet-Tschudi, "Potential mechanisms of development-dependent adverse effects of the herbicide paraquat in 3d rat brain cell cultures," *NeuroToxicology*, vol. 60, pp. 116–124, 2017.

[6] F. J. Pierce and P. Nowak, "Aspects of precision agriculture," in *Advances in Agronomy*, pp. 1–85, Elsevier, 1999.

[7] J. S. Duhan, R. Kumar, N. Kumar, P. Kaur, K. Nehra, and S. Duhan, "Nanotechnology: The new perspective in precision agriculture," *Biotechnology Reports*, vol. 15, pp. 11–23, 2017.

[8] M. Srbinovska, C. Gavrovski, V. Dimcev, A. Krkoleva, and V. Borozan, "Environmental parameters monitoring in precision agriculture using wireless sensor networks," *Journal of Cleaner Production*, vol. 88, pp. 297–307, 2015.

[9] M. D. Bah, A. Hafiane, and R. Canals, "Weeds detection in UAV imagery using SLIC and the hough transform," in *2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)*, IEEE, 2017.

[10] H.-D. Seelig, A. Hoehn, L. Stodieck, D. Klaus, W. Adams, and W. Emery, “Relations of remote sensing leaf water indices to leaf water thickness in cowpea, bean, and sugarbeet plants,” *Remote Sensing of Environment*, vol. 112, no. 2, pp. 445–455, 2008.

[11] E. Adam, O. Mutanga, and D. Rugege, “Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review,” *Wetlands Ecology and Management*, vol. 18, no. 3, pp. 281–296, 2009.

[12] K. S. He, D. Rocchini, M. Neteler, and H. Nagendra, “Benefits of hyperspectral remote sensing for tracking plant invasions,” *Diversity and Distributions*, vol. 17, no. 3, pp. 381–392, 2011.

[13] S. Schmidtlein, H. Feilhauer, and H. Bruelheide, “Mapping plant strategy types using remote sensing,” *Journal of Vegetation Science*, vol. 23, no. 3, pp. 395–405, 2011.

[14] M. Prabhakar, Y. G. Prasad, and M. N. Rao, “Remote sensing of biotic stress in crop plants and its applications for pest management,” in *Crop Stress and its Management: Perspectives and Strategies*, pp. 517–545, Springer Netherlands, 2011.

[15] Y. Huang, S. J. Thomson, W. C. Hoffmann, Y. Lan, and B. K. Fritz, “Development and prospect of unmanned aerial vehicle technologies for agricultural production management,” *International Journal of Agricultural and Biological Engineering*, vol. 6, no. 3, pp. 1–10, 2013.

[16] P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T. K. Alexandridis, and G. Zalidis, “An autonomous multi-sensor UAV system for reduced-input precision agriculture applications,” in *2016 24th Mediterranean Conference on Control and Automation (MED)*, IEEE, 2016.

[17] B. H. Y. Alsalam, K. Morton, D. Campbell, and F. Gonzalez, “Autonomous UAV with vision based on-board decision making for remote sensing and precision agriculture,” in *2017 IEEE Aerospace Conference*, IEEE, 2017.

[18] C. Zhang and J. M. Kovacs, “The application of small unmanned aerial systems for precision agriculture: a review,” *Precision Agriculture*, vol. 13, no. 6, pp. 693–712, 2012.

[19] E. Hamuda, M. Glavin, and E. Jones, “A survey of image processing techniques for plant extraction and segmentation in the field,” *Computers and Electronics in Agriculture*, vol. 125, pp. 184–199, 2016.

[20] A. Tellaeche, X. P. Burgos-Artizzu, G. Pajares, and A. Ribeiro, “A vision-based method for weeds identification through the bayesian decision theory,” *Pattern Recognition*, vol. 41, no. 2, pp. 521–530, 2008.

[21] K. Kirk, H. J. Andersen, A. G. Thomsen, J. R. Jørgensen, and R. N. Jørgensen, “Estimation of leaf area index in cereal crops using red-green images,” *Biosystems Engineering*, vol. 104, no. 3, pp. 308–317, 2009.

[22] H. Y. Jeon, L. F. Tian, and H. Zhu, “Robust crop and weed segmentation under uncontrolled outdoor illumination,” *Sensors*, vol. 11, pp. 6270–6283, June 2011.

[23] N. Otsu, “A threshold selection method from gray-level histograms,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62–66, 1979.

[24] J. A. Marchant, R. D. Tillett, and R. Brivot, “Real-time segmentation of plants and weeds,” *Real-Time Imaging*, vol. 4, no. 4, pp. 243–253, 1998.

[25] J. Reid and S. Searcy, “Vision-based guidance of an agriculture tractor,” *IEEE Control Systems Magazine*, vol. 7, no. 2, pp. 39–43, 1987.

[26] L. F. Tian and D. C. Slaughter, “Environmentally adaptive segmentation algorithm for outdoor image segmentation,” *Computers and Electronics in Agriculture*, vol. 21, no. 3, pp. 153–168, 1998.

[27] J. Guerrero, G. Pajares, M. Montalvo, J. Romeo, and M. Guijarro, “Support vector machines for crop/weeds identification in maize fields,” *Expert Systems with Applications*, vol. 39, no. 12, pp. 11149–11155, 2012.

[28] L. Zheng, J. Zhang, and Q. Wang, “Mean-shift-based color segmentation of images containing green vegetation,” *Computers and Electronics in Agriculture*, vol. 65, no. 1, pp. 93–98, 2009.

[29] W. Guo, U. K. Rage, and S. Ninomiya, "Illumination invariant segmentation of vegetation for time series wheat images based on decision tree model," *Computers and Electronics in Agriculture*, vol. 96, pp. 58–66, 2013.

[30] Z. Yu, Z. Cao, X. Wu, X. Bai, Y. Qin, W. Zhuo, Y. Xiao, X. Zhang, and H. Xue, "Automatic image-based detection technology for two critical growth stages of maize: Emergence and three-leaf stage," *Agricultural and Forest Meteorology*, vol. 174-175, pp. 65–84, 2013.

[31] L. Zheng, D. Shi, and J. Zhang, "Segmentation of green vegetation of crop canopy images based on mean shift and fisher linear discriminant," *Pattern Recognition Letters*, vol. 31, no. 9, pp. 920–925, 2010.

[32] X. Bai, Z. Cao, Y. Wang, Z. Yu, X. Zhang, and C. Li, "Crop segmentation from images by morphology modeling in the CIE l*a*b* color space," *Computers and Electronics in Agriculture*, vol. 99, pp. 21–34, 2013.

[33] X. Bai, Z. Cao, Y. Wang, Z. Yu, Z. Hu, X. Zhang, and C. Li, "Vegetation segmentation robust to illumination variations based on clustering and morphology modelling," *Biosystems Engineering*, vol. 125, pp. 80–97, 2014.

[34] J. Torres-Sánchez, F. López-Granados, and J. Peña, "An automatic object-based method for optimal thresholding in UAV images: Application for vegetation detection in herbaceous crops," *Computers and Electronics in Agriculture*, vol. 114, pp. 43–52, 2015.

[35] G. E. Meyer and J. C. Neto, "Verification of color vegetation indices for automated crop imaging applications," *Computers and Electronics in Agriculture*, vol. 63, no. 2, pp. 282–293, 2008.

[36] J. M. Pena, J. Torres-Sanchez, A. I. de Castro, M. Kelly, and F. L. Granados, "Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (uav) images," *PLOS One*, vol. 8, no. 10, p. e77151, 2013.

[37] C. Gee, J. Bossu, G. Jones, and F. Truchetet, "Crop/weed discrimination in perspective agronomic images," *Computers and Electronics in Agriculture*, vol. 60, no. 1, pp. 49–59, 2008.

[38] M. Montalvo, G. Pajares, J. Guerrero, J. Romeo, M. Guijarro, A. Ribeiro, J. Ruz, and J. Cruz, "Automatic detection of crop rows in maize fields with high weeds pressure," *Expert Systems with Applications*, vol. 39, no. 15, pp. 11889–11897, 2012.

[39] T. Bakker, H. Wouters, K. van Asselt, J. Bontsema, L. Tang, J. Müller, and G. van Straten, "A vision based row detection system for sugar beet," *Computers and Electronics in Agriculture*, vol. 60, no. 1, pp. 87–95, 2008.