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Algorithm to Estimate Sorghum Grain Number from Panicles Using Images Collected with a Smartphone at Field-Scale

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Summary

An estimation of on-farm yield before harvest is important to help farmers make decisions about additional input use, time to harvest, and options for end uses of the harvestable product. However, obtaining a rapid assessment of on-farm yield can be challenging, especially for a sorghum (*Sorghum bicolor* L.) crop due to the complexity of counting the total number of grains in a panicle at field-scale. One alternative to reduce labor is to develop a rapid assessment method employing computer vision algorithms. Computer vision has already been utilized to account for the number of grains within a panicle, yet it has only been tested under controlled conditions. The objective of this study was to estimate the number of grains in a sorghum panicle using imagery data captured from a smartphone device at field-scale. During the pre-harvest season, sorghum panicles of several commercial hybrids were photographed in the field. Later, the plants corresponding to those panicles were harvested to determine the final number of grains, to develop a benchmarking dataset. Using Python language and the OpenCV library, each image was filtered, blurred, and contours were applied to estimate the number of grains in each sorghum panicle. The absolute mean difference obtained using the algorithm output for the observed and the estimated number of grains was 570 (root mean square percentage error = 53%).

Introduction

Production estimations are valuable information for farmers (Fountas et al., 2015). For sorghum, an attempt to estimate grain numbers using a traditional and imagery approach has been done but not transferred at field-scale (Ciampitti et al., 2014; 2015). One alternative to estimate production relies on the usage of computer vision algorithms (Wan and Goudos, 2020) to generate meaningful information from images and videos (Davies, 2005). The usage of computer vision is already established in several knowledge areas such as medicine (Dey et al., 2021), industry (Kakani et al., 2020), and agriculture (Mogili and Deepak, 2018). In agriculture, computer vision is mostly used to determine diseases (Liu et al., 2016), quality (Olgun et al., 2016), phenology (Naik et al., 2017), nutritional status (Romualdo et al., 2014), and production estimates (Ramos et al., 2017). Komyshev et al. (2017) evaluated the use of imagery documenting the estimation of sorghum grain number under controlled conditions. However, to assist farmers in their estimates of crop production, the process of counting grains must migrate from a laboratory environment to field applications (Fernandez-Gallego et al., 2018). Following this rationale, the aim of this study was to estimate the number of grains from a sorghum panicle using images collected with a smartphone at field-scale.

Procedures

Image Capture and Measurements

A total of 100 sorghum plants from different hybrids (five plants per hybrid) were selected during the pre-harvest (October 2022), KS, U.S. Two pictures of each plant were collected without removing the panicle from the plant. The pictures centralized a single panicle in the image, with the presence of other plants in the background. After the images were taken, the sorghum panicles were harvested, and grains were counted manually. A generic smartphone was used with a camera of 64 MP and set on automatic mode of image capture. In all images, the sunlight was in the same direction as the camera.

Image Processing and Models Generation

All the images were cropped centering the sorghum panicle in a 9:16 ratio frame rectangle. Later, the images were separated into two groups: white and red sorghum panicles (160 red sorghum and 40 white sorghum). Using Python (Van Rossum and Drake, 2009) and OpenCV library (Bradski, 2000), color filter, blur, and contouring processes were adjusted for each sorghum group. This adjustment was done considering the absolute mean difference between the observed and the estimated number of grains. As an example of the process, Figure 1A shows an untreated image taken at field-scale. Figure 1B shows the same image after the filter and blurring processes have been applied. In Figure 1C, the contours were applied to the image after the filter and blurring processes. Finally, the grain number per panicle was estimated by counting the number of contours.

Results

Figure 2 shows a scatter plot associating the observed and the algorithm estimation for sorghum grain number. The root mean square percentage error (RMSPE) was 53% and the difference between the observed and estimated number of grains in a panicle head was 570. This difference represents ~24% of the total number of grains in an average panicle.

Conclusions

The algorithm produced in this study represents the first attempt to estimate the grain number from sorghum panicles using images captured from a smartphone device at field-scale. An adequate estimation of sorghum grain number was achieved (relative high values of RMSPE). Future works should focus on developing an artificial intelligence model to recognize one panicle per image; and embed the whole algorithm into a mobile app.

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References

Bradski, G. (2000). The OpenCV Library. Dr. Dobb's Journal of Software Tools.

Ciampitti IA, Azevedo AJ, Balboa GR, Bossio N. 2015. Sorghum yield app, a new tool for predicting sorghum yields: validation and calibration. ASA, CSSA, and SSSA International Annual Meeting (2015). Poster Number: 501. *https://scisoc.confex.com/crops/2015am/webprogram/Paper93787.html*

Ciampitti IA, Balboa GR, Prasad PVV. 2014. Development of a new tool for estimating sorghum yields at the farm-scale. ASA, CSSA, and SSSA International Annual Meeting (2014). Poster Number: 342. *https://scisoc.confex.com/scisoc/2014am/webprogram/Paper88108.html*

Davies, E.R. (Ed.), 2005. Machine Vision, in: Machine Vision (Third Edition), Signal Processing and Its Applications. Morgan Kaufmann, Burlington, p. i. *https://doi.org/10.1016/B978-0-12-206093-9.50039-3*

Dey, S., Konar, D., De, S., Bhattacharyya, S., 2021. Chapter 1 - An introductory illustration of medical image analysis, in: Gandhi, T., Bhattacharyya, S., De, S., Konar, D., Dey, S. (Eds.), Advanced Machine Vision Paradigms for Medical Image Analysis, Hybrid Computational Intelligence for Pattern Analysis and Understanding. Academic Press, pp. 1–9. *https://doi.org/10.1016/B978-0-12-819295-5.00001-9*

Fernandez-Gallego, J.A., Kefauver, S.C., Gutiérrez, N.A., Nieto-Taladriz, M.T., Araus, J.L., 2018. Wheat ear counting in-field conditions: high throughput and low-cost approach using RGB images. Plant Methods 14, 22. *https://doi.org/10.1186/s13007-018-0289-4*

Fountas, S., Carli, G., Sørensen, C.G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., Liakos, B., Canavari, M., Wiebensohn, J., Tisserye, B., 2015. Farm management information systems. Comput. Electron. Agric. 115, 40–50. *https://doi.org/10.1016/j.compag.2015.05.011*

Kakani, V., Nguyen, V.H., Kumar, B.P., Kim, H., Pasupuleti, V.R., 2020. A critical review on computer vision and artificial intelligence in food industry. Journal of Agriculture and Food Research 2, 100033. *https://doi.org/10.1016/j.jafr.2020.100033*

Komyshev, E., Genaev, M., Afonnikov, D., 2017. Evaluation of the SeedCounter, A Mobile Application for Grain Phenotyping. Frontiers in Plant Science 7.

Liu, T., Chen, W., Wu, W., Sun, C., Guo, W., Zhu, X., 2016. Detection of aphids in wheat fields using a computer vision technique. Biosystems Engineering 141, 82–93. *https://doi.org/10.1016/j.biosystemseng.2015.11.005*

Mogili, U.R., Deepak, B.B.V.L., 2018. Review on Application of Drone Systems in Precision Agriculture. Procedia Computer Science 133, 502–509. *https://doi.org/10.1016/j.procs.2018.07.063*

Naik, H.S., Zhang, J., Lofquist, A., Assefa, T., Sarkar, S., Ackerman, D., Singh, A., Singh, A.K., Ganapathysubramanian, B., 2017. A real-time phenotyping framework using machine learning for plant stress severity rating in soybean. Plant Methods 13, 23. *https://doi.org/10.1186/s13007-017-0173-7*

Olgun, M., Onarcan, A.O., Özkan, K., Işik, Ş., Sezer, O., Özgişi, K., Ayter, N.G., Başçiftçi, Z.B., Ardiç, M., Koyuncu, O., 2016. Wheat grain classification by using dense SIFT features with SVM classifier. Computers and Electronics in Agriculture 122, 185–190. *https://doi.org/10.1016/j.compag.2016.01.033*

Pedregosa *et al.* Scikit-learn: Machine Learning in Python, Journal of Machine Learning Research, 12, pp. 2825-2830, 2011.

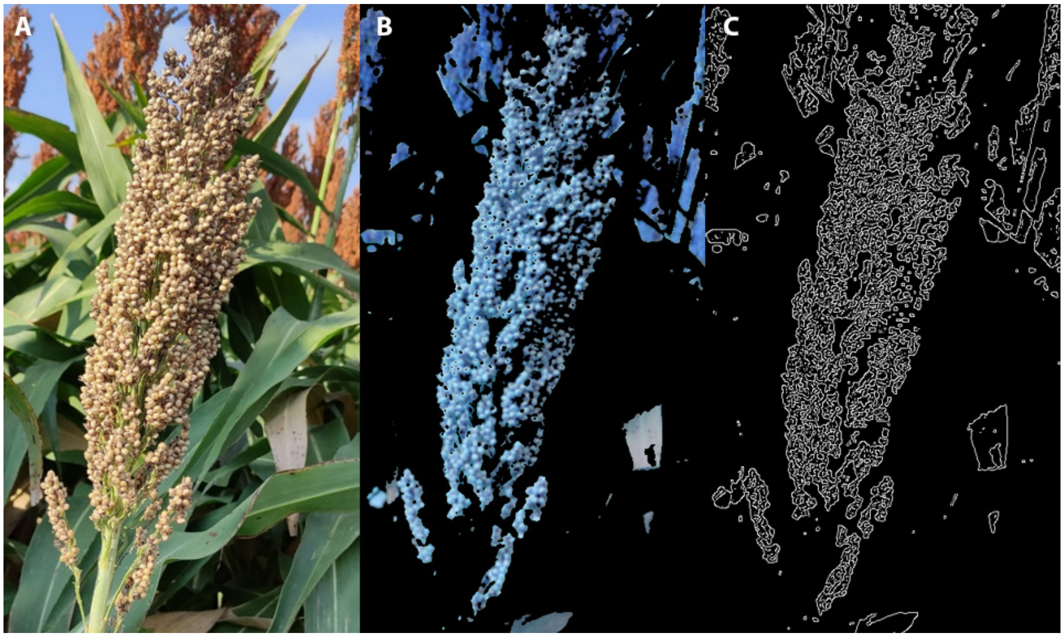
Ramos, P.J., Prieto, F.A., Montoya, E.C., Oliveros, C.E., 2017. Automatic fruit count on coffee branches using computer vision. Computers and Electronics in Agriculture 137, 9–22. *https://doi.org/10.1016/j.compag.2017.03.010*

Rigon, J.P.G., Capuani, S., Fernandes, D.M., Guimarães, T.M., 2016. A novel method for the estimation of soybean chlorophyll content using a smartphone and image analysis. Photosynthetica 54, 559–566. *https://doi.org/10.1007/s11099-016-0214-x*

Romualdo, L.M., Luz, P.H.C., Devechio, F.F.S., Marin, M.A., Zúñiga, A.M.G., Bruno, O.M., Herling, V.R., 2014. Use of artificial vision techniques for diagnostic of nitrogen nutritional status in maize plants. Computers and Electronics in Agriculture 104, 63–70. *https://doi.org/10.1016/j.compag.2014.03.009*

Wan, S., Goudos, S., 2020. Faster R-CNN for multi-class fruit detection using a robotic vision system. Comput. Netw. 168. *https://doi.org/10.1016/j.comnet.2019.107036*

Van Rossum, G., & Drake, F. L. (2009). Python 3 Reference Manual. Scotts Valley, CA: CreateSpace. Figure 1. (A) Image of sorghum panicle captured in field, (B) image after color filtering and blurring process, and (C) image after contours applied.



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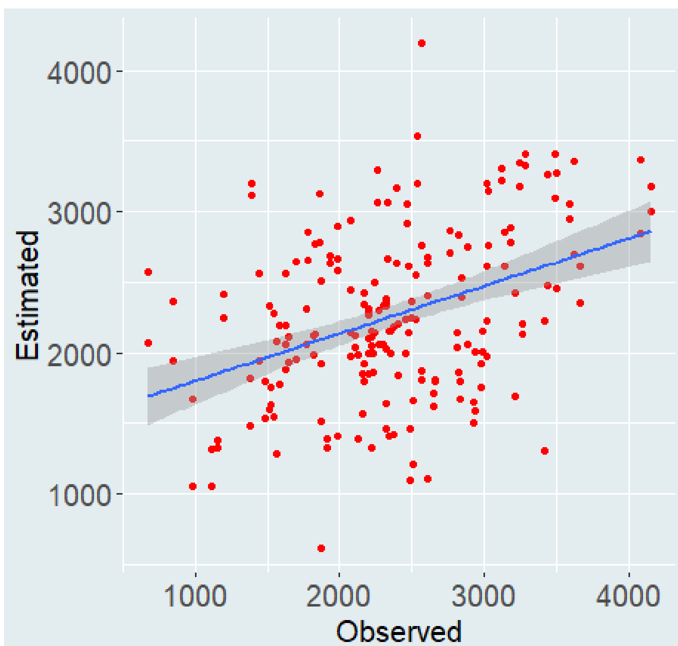

Figure 2. Scatter plot of Estimated vs. Observed using the estimation obtained from the algorithm.