Editorial

Computer Vision Problems in Plant Phenotyping, CVPPP 2017

Introduction to the CVPPP 2017 workshop papers

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Plant phenotyping is the identification of effects on the phenotype (i.e., the plant appearance and behavior) as a result of genotype differences (i.e., differences in the genetic code) and the environment. Previously, the process of taking phenotypic measurements has been laborious, costly, and time consuming. In recent years, non-invasive, image-based methods have become more common. These images are recorded by a range of capture devices from small embedded camera systems to multi-million Euro smart-greenhouses, at scales ranging from microscopic images of cells, to entire fields captured by UAV imaging. These images needs to be analyzed in a high throughput, robust, and accurate manner.

UN-FAO statistics show that according to current population predictions we will need to achieve a 70% increase in food productivity by 2050, simply to maintain current global agricultural demands. Phenomics – large-scale measurement of plant traits – is a key bottleneck in the knowledge-based bioeconomy, and machine vision is ideally placed to help [10]. However, the challenges arising differ the from usual tasks addressed by the computer vision community, due to the requirements posed by this application scenario.

Dealing with these new problems has spawned specialized workshops such as Computer Vision Problems in Plant Phenotyping (CVPPP) and the stand-alone workshop IAMPS (Image Analysis Methods for the Plant Sciences) now in its fourth year. CVPPP was held for the first time in conjunction with the European Conference on Computer Vision (ECCV) 2014 and the second time with the British Machine Vision Conference (BMVC) 2015, CVPPP 2017 was held in conjunction with the International Conference on Computer Vision (ICCV).

The overriding goal of this workshop is to not only present interesting computer vision solutions, but also to introduce challenging computer vision problems in the increasingly important plant phenotyping domain, accompanied with benchmark datasets and suitable performance evaluation methods.

Together with the workshop, the 3rd edition of the leaf counting (LCC) and leaf segmentation challenge (LSC) took place https://www.plant-phenotyping.org/CVPPP2017-challenge.

In the following we briefly describe the papers received in the main call and the challenge[1].

1. Regular call

Of the eight papers presented in CVPPP 2017, six [3, 4, 7, 11, 12, 13] responded to an open call and two [1, 5] to the LCC challenge (see below). All submissions, including short papers and extended abstracts, were double-blind peer reviewed by at least two external reviewers. The committee then ranked papers and rejected those that did not receive sufficient scores of quality and priority as suggested by the reviewers. Overall, at present the program includes 8 full papers that are presented as lighting talks and posters. In addition, 12 short papers are presented as posters. The full schedule and links to papers are available at: https://www.plant-phenotyping.org/CVPPP2017.

This year, beneath classic image processing approaches to plant phenotyping applications [3, 4], there has been particular interest in deep learning [1, 5, 7, 11] and 3D methods [12, 13].

2. Challenge

This year's challenge included the 3rd edition of the Leaf Segmentation Challenge and the 2nd edition of the Leaf

[1]The papers listed herein are correct as of the camera-ready deadline [Aug 24, 2017]. The workshop website (https://www.plant-phenotyping.org/CVPPP2017) contains the most up to date paper list.

Counting Challenge. Data from [9] were used again as in previous years. However, a new dataset (A4) was included which, whilst already in the public domain [2], was edited and formatted to match the style of the other available data and thus be more suitable for the challenge. Also a new 'blind' set (A5) was created that essentially repackaged the data but obscured the origin of the dataset.

The call was disseminated via several public and private lists and advertised on several computer vision websites.

We received 20 registrations and download requests for the training and testing datasets. Four teams submitted results for the Leaf Counting Challenge, along with four papers. All papers were double blind reviewed as before. Two submissions were accepted as full papers [1, 5]. Unsurprisingly, three out of the four attempts, involved the use of deep learning and specifically convolutional neural networks. At the time of the conclusion of the challenge, the table below compares the performance of this year's submissions [1, 5] with the winner of the last LCC in 2015 [6].

	Data set	Count-Diff	AbsCount-Diff	Agreement [%]	MSE
[5]	A1	-0.39(1.17)	0.88(0.86)	33.3	1.48
	A2	-0.78(1.64)	1.44(1.01)	11.1	3.00
	A3	0.13(1.55)	1.09(1.10)	30.4	2.38
	A4	0.29(1.10)	0.84(0.76)	34.5	1.28
	A5	0.25(1.21)	0.90(0.85)	33.2	1.53
	All	0.19(1.24)	0.91(0.86)	32.9	1.56
[1]	A1	-0.33(1.38)	1.00(1.00)	30.3	1.97
	A2	-0.22(1.86)	1.56(0.88)	11.1	3.11
	A3	2.71(4.58)	3.46(4.04)	7.1	28.00
	A4	0.23(1.44)	1.08(0.97)	29.2	2.11
	A5	0.80(2.77)	1.66(2.36)	23.8	8.28
	All	0.73(2.72)	1.62(2.30)	24.0	7.90
[6]	A1	-0.79(1.54)	1.27(1.15)	27.3	2.91
	A2	-2.44(2,88)	2.44(2.88)	44.4	13.33
	A3	-0.04(1.93)	1.36(1.37)	19.6	3.68

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References

[1] S. Aich and I. Stavness. Leaf counting with deep convolutional and deconvolutional networks. In *[8]*, 2017. 1, 2

[2] J. Bell and H. M. Dee. Aberystwyth leaf evaluation dataset, Nov. 2016. 2

[3] Y. Chen, J. Ribera, C. Boomsma, and E. Delp. Locating crop plant centers from uav-based rgb imagery. In *[8]*, 2017. 1

[4] S. D. Choudhury, S. Goswami, S. Bashyam, A. Samal, and T. Awada. Automated stem angle determination for temporal plant phenotyping analysis. In *[8]*, 2017. 1

[5] A. Dobrescu, M. V. Giuffrida, and S. Tsaftaris. Leveraging multiple datasets for deep leaf counting. In *[8]*, 2017. 1, 2

[6] M. V. Giuffrida, M. Minervini, and S. Tsaftaris. Learning to count leaves in rosette plants. In S. A. Tsaftaris, H. Scharr, and T. Pridmore, editors, *Proceedings of the Computer Vision Problems in Plant Phenotyping (CVPPP)*, pages 1.1–1.13. BMVA Press, 9 2015. 2

[7] M. V. Giuffrida, H. Scharr, and S. Tsaftaris. Arigan: Synthetic arabidopsis plants using generative adversarial network. In *[8]*, 2017. 1

[8] *2017 IEEE International Conference on Computer Vision Workshop (ICCVW)*, Venice, Italy, Oct. 2017. IEEE Computer Society. 2

[9] M. Minervini, A. Fischbach, H. Scharr, and S. A. Tsaftaris. Finely-grained annotated datasets for image-based plant phenotyping. *Pattern Recognition Letters*, 81:80 – 89, 2016. 2

[10] M. Minervini, H. Scharr, and S. A. Tsaftaris. Image analysis: The new bottleneck in plant phenotyping. *IEEE Sign. Proc. Mag.*, 32(4):126–131, July 2015. 1

[11] M. P. Pound, J. Atkinson, D. Wells, T. Pridmore, and A. French. Deep learning for multi-task plant phenotyping. In *[8]*, 2017. 1

[12] S. Srivastava, S. Bhugra, B. Lall, and S. Chaudhary. Drought stress classification using 3d plant models. In *[8]*, 2017. 1

[13] H. Uchiyama, S. Sakurai, M. Mishima, D. Arita, T. Okayasu, A. Shimada, and R. T. Kyushu. An easy-to-setup 3d phenotyping platform for Komatsuna dataset. In *[8]*, 2017. 1