Deep Neural Networks for Root System Analysis

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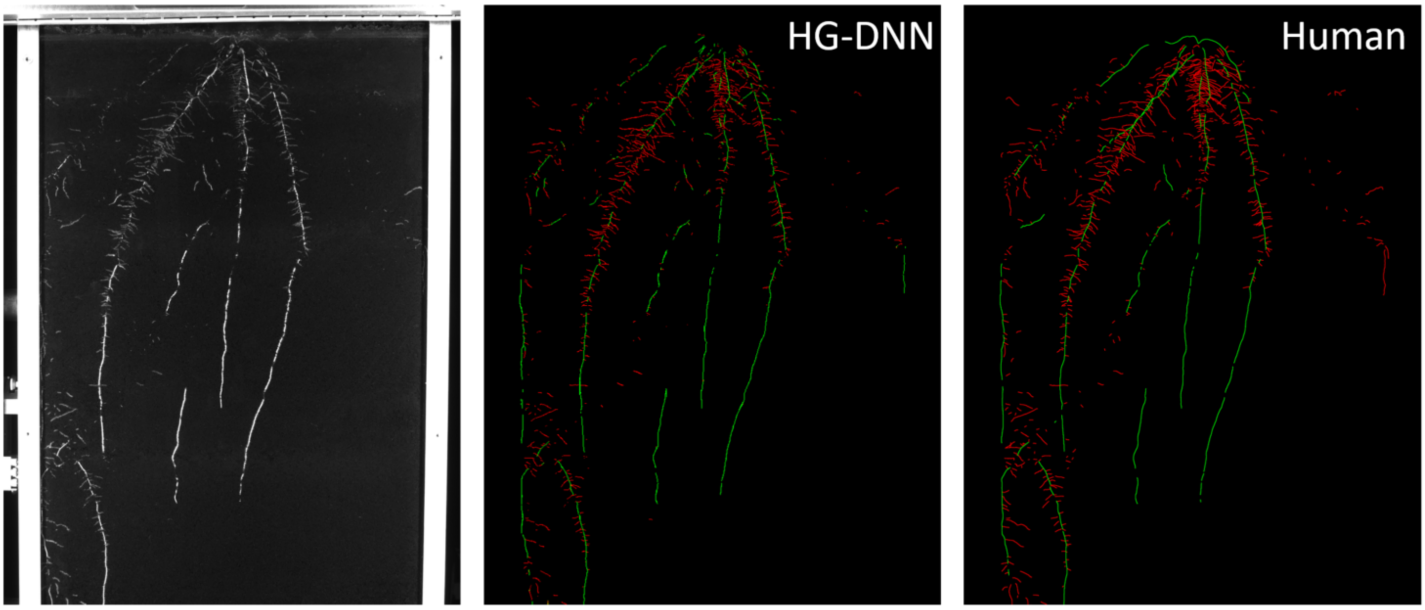

Figure 1: Typical rhizotron data and results. Left: input image. Middle: automatic labelling result. Right: manually labelled image. Main roots are green, side root red.

In this contribution we describe a deep neural network (DNN) solution for labelling of roots according to their root order, *i.e.* main or side-root.

A wide range of image-based plant phenotyping methods for above-ground organs exist, where automated camera-based methods are abundant [3, 5, 14, 15]. For below-ground organs like root systems noninvasive measurements require either growing plants in special ways, like in transparent agar [8], on paper [2] or in hydro- or aeroponics. Or special 3D imaging equipment is required when grown in soil, *e.g.* magnetic resonance imaging (MRI) [12], positron emission tomography (PET) [4], or computed tomography (CT) [7]. Simple camera-based imaging of root systems in soil can be achieved, when using special flat pots, so-called rhizotrons [9], where one side is made from transparent material. During plant growth they are inclined such that roots grow along the transparent window. In contrast to other above mentioned root system imaging setups where the full root system is visible, rhizotron imagery shows only fragments of the root system, as roots growing along the window vanish into the opaque soil from time to time. Well established root image analysis solutions (like *e.g.* [6, 13]) are designed to reconstruct complete root graphs, thus not being suitable in this application scenario. Due to this lack of fully automated, high quality solutions state-of-the-art analysis still involves some human post-processing or labelling.

Human generated labels are 1 pixel wide lines indicating where roots are, *i.e.* labelled root skeletons, rather than segmentations. Drawing precision is in the range of few pixels, therefore skeletons are not always reliably centered on roots, introducing some position noise in the labels. Having such hand-labelled data available, enables us to investigate different DNN architectures for root labelling. Biologically relevant root system parameters like branching angles or -frequencies, root densities etc. are then derived in a subsequent step.

We investigate two different DNN architectures. The first one is a modification of the four-fold hourglass introduced by [10] and established for plant phenotyping applications like grain, ear or ear tip detection [11]. This network is designed for heat-map generation, indicating where sough for objects are in an image. There, training is performed using mean square error as loss. Here, we appended softmax layers at each layer used for loss calculation, such that pixel-wise classification can be learned using categorical cross entropy. The network was trained end-to-end, from scratch, using RMSProp with batch size 50, 100 epochs and learning rate $2.5 \cdot 10^{-4}$ as in [11]. As image data is typically 15Mpix, we employed tiling such that outputs are 64×64 as in [11] in order to make the network trainable on a single Nvidia 1080Ti GPU with 11GB memory. The resulting network has 25M parameters.

Results using the four-fold hourglass architecture are shown in Figure 1. The general root system properties are already very well captured. However, there is still room for improvement, compare *e.g.* the topmost main roots not being completely captured by the DNN.

In order to enlarge spatial reach, in an ongoing project, we currently investigate a DNN architecture introduced for fast image processing [1] using dilated convolutions [16]. Using the same GPU for training, the smaller size of the network allows for larger tiles, 320×320 in our case. Preliminary results are comparable to the ones shown in Figure 1, while the network has only in the order of 100k parameters.

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