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Upper limit for context–based crop classification in robotic weeding applications

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Knowledge of the precise position of crop plants is a prerequisite for effective mechanical weed control in robotic weeding application such as in crops like sugar beets which are sensitive to mechanical stress. Visual detection and recognition of crop plants based on their shapes has been described many times in the literature. In this paper the potential of using knowledge about the crop seed pattern is investigated based on simulated output from a perception system. The reliability of position–based crop plant detection is shown to depend on the weed density (ρ, measured in weed plants per square metre) and the crop plant pattern position uncertainty (σ_x and σ_y, measured in metres along and perpendicular to the crop row, respectively). The recognition reliability can be described with the positive predictive value (PPV), which is limited by the seeding pattern uncertainty and the weed density according to the inequality: $\text{PPV} \le (1 + 2\pi\rho\sigma_x\sigma_y)^{-1}$. This result matches computer simulations of two novel methods for position–based crop recognition as well as earlier reported field–based trials.

1. Introduction

Typical work flows in agriculture are often based on crop plants placed in row structures. Cereals like barley and wheat are placed in rows with no clear structure within the row, whilst maize, sugar beets and other high value crops are placed in rows with a clear defined intra-row spacing between crop plants, see Fig. 1. Given the position of a single sugar beet plant, it is possible to predict locations of nearby crop plants, based on information about plant distances within the row. With information about crop plant locations systems such as the Garfords Robocrop (Garford, 2011) and the Robovator by F. Poulsen Engineering (Frank Poulsen Engineering, 2014) can control weeds in the crop row using mechanical means. The capacity of both the current mechanical weeding robots is around 4 ha h^{-1}.

In robotic weeding applications plant recognition is often based on machine vision either using spectral properties or plant morphology/shape information (Slaughter, Giles, &

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Nomenclature

x	Coordinate along x-axis (direction along the crop row), $x = 0$ is the expected crop location, m
y	Coordinate along y-axis (perpendicular to the crop row), $y = 0$ is the expected crop location, m
σ_x	Crop position uncertainty along the x-axis, m
σ_y	Crop position uncertainty along the y-axis, m
α	Scaling factor, 1
ρ	Weed density, m^{-2}
λ, NWP	Normalised weed pressure, 1
$p_{\sigma_c}(c)$	Position probability distribution of variable c, 1
$n_w(x,y)$	Expected number of weeds closer to the seeding location than the point (x,y), 1
$\vec{x}_k$	Coordinates of the kth plant, m
$\vec{x}_{offset}$	Coordinates of the first crop plant in the row structure, m
$\vec{d}$	Vector from one crop position to the next expected crop position, m
k, i, m	Index variables, 1
l	Number of occurrences in a Poisson distribution, 1
c_i	Position score associated to the ith plant, 1
s	Scaling factor, 1
N	Number of neighbour positions to examine, 1
Φ	Probability of not seeing any plants within 3σ, 1
γ	Crop emergence, 1
f	Fitting parameter for classifier performance, 1
PPV	Positive prediction value, 1
ePPV	Expected positive prediction value, 1
oPPV	Observed positive prediction value, 1
n_{crop}	Number of crop plants in dataset, 1
n_{weed}	Number of weed plants in dataset, 1
n_{total}	Total number of plants in dataset, 1
$f(l, \beta)$	Probability of seeing l events in a Poisson process with an average number of events of β, 1
x_n	nth crop location, m
n	Crop plant number, 1
$\sigma_{seed-plant}$	Deviance between seed placement and resulting plant position, m

Abbreviation

TP	True positives
FP	False positives
TN	True negatives
FN	False negatives
CI	Credible interval

Downey, 2008). Various shape descriptors (compactness, Hu moments, skeleton features, …) were used by Weis and Gerhards (2008) to map weed infestations. Giselsson, Midtiby, and Jørgensen (2013) used shape features derived from distance maps to distinguish between two groups of seedlings. Active shape models were used by Søgaard (2005) to recognise three different weed species. Plant classification based on spectral properties (Zwiggelaar, 1998) and plant morphology (Weis & Sökefeld, 2010) are vulnerable to variations in plant appearance. There can be a large variation of plant appearance within a field, between fields and during growth season. Also weed pressures and populations vary. However, the sowing pattern is more stable. Therefore, it is interesting to use classifiers that utilise the position information to discriminate between crops and weeds.

Tillett (2001) used crop position information to distinguish between crop and weed plants in a field of *brassica*. The crops were transplanted to a square pattern with side lengths of 0.48 m in three adjacent rows. It was stated that it is practical to track crop plants using extended Kalman filtering, but numbers of the achieved classification rate were given. Onyango and Marchant (2003) detected grid placement of cauliflower and used this information to distinguish between crop and weed pixels. The highest obtained correct crop and weed pixel classification rates were 96% and 92%.

The two earlier examples looked at plants placed in a 2D pattern, while Åstrand and Baerveldt (2004) used crop position information in a single row to classify crop and weed plants in sugar beet fields. In a field with a weed pressure of 50 plants m^{-2}, they correctly recognised 96% of the crop plants by searching for a pattern consisting of five plants placed in a row structure with the inter–plant distance set to the known crop–plant distance. In Åstrand (2005) position information was combined with individual plant features for recognising crop plants. In field conditions with low weed pressure (50 plants m^{-2}) they achieve a positive predictive value (PPV) of 74% for recognising crops when only using plant position information. When the weed pressure is increased to 400 plants m^{-2} the PPV decreases to 47%. In both cases the crop emergence were around 70%. This decrease is explained by increase of plant occlusion/overlapping to the effect that the row structure can be difficult to recognise when the number of weed plants is large. Crop plant localisation in single crop rows were also investigated by Bontsema, van Asselt, Lempens, and van Straten (1998) who used frequency filtering of the amount of vegetation in the crop row to locate individual crop plants.

Recent papers by Cordill and Grift (2011) and Chen et al. (2013) also relied on recognising crop plants by knowing the distance between adjacent plants. Cordill and Grift (2011) used four laser beams to measure maize stalk placements, the measurements were then passed through two filters (based on stalk width and distance to last located maize plant) that recognised the crop plants. Chen et al. (2013) used a stereo camera setup to get images of maize plants at the two–three leaf stage. Plants with heights lower than a given threshold were then excluded and in the remaining plants they searched for plants with a fixed distance of 250 mm ± 25 mm.

The papers cited above show that plant position information can be used for recognising crop plants sown in a known pattern when using different perception systems. In this paper the upper limit of what can be achieved by using information about sowing geometry and plant positions is investigated. The system is not limited to vision–based perception systems as it can also use input from e.g. a lidar.

One measure of how good a system that recognises crop plants performs is the probability that a crop marked as a crop plant in fact is a crop plant, this value is denoted the PPV. Theoretical considerations show that the PPV is bounded upwards by the expression $\frac{1}{1+\lambda}$ where λ is the normalised weed