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Research Paper

Automatic detection of curved and straight crop rows from images in maize fields

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A new method for detecting curved and straight crop rows in images captured in maize fields during the initial growth stages of crop and weed plants is proposed. The images were obtained under perspective projection with a camera installed on board and conveniently arranged at the front part of a tractor. The final goal is the identification of the crop rows with two purposes: a) precise autonomous guidance; b) site-specific treatments, including weed removal, where weeds are identified as plants outside the crop rows. Image quality is affected by uncontrolled lighting conditions in outdoor agricultural environments and gaps along the crop rows due to lack of germination or defects during planting. Also, different crop and weed plant heights and volumes appear at different growth stages affecting the crop row detection process. The proposed method was designed with the required robustness to cope with the above situations and consists of three linked phases: (i) image segmentation, (ii) identification of starting points for determining the beginning of the crop rows and (iii) crop rows detection. The main contribution of the method is the ability to detect curved and straight crop rows having regular or irregular inter-row spacing, even when both row types coexist in the same field and image. The performance of the proposed approach was quantitatively compared against six existing strategies, achieving accuracies between 86.3% and 92.8%, depending on whether crop rows were straight/curved with regular or irregular spacing, with processing times less than 0.64 s per image.

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Nomenclature

Abbreviations

CRD	crop row detection
CRDA	crop row detection accuracy
CRDA*	slight variant of CRDA
DAGP	detection by accumulation of green pixels
DBMR	detection based on micro-ROIs
ExG	excess green
GNSS	global navigation satellite systems
GPS	global positioning system
HT	Hough transform
LRQ	linear regression based on least squares
LTS	linear regression based on the Theil-Shen estimator
RHEA	robotics and associated high-technologies and equipment for agriculture and forestry
ROI	region of interest
RTK-GPS	real time kinematics-global positioning system
TMGEM	template matching followed by global energy minimisation

Symbols

A	number of white pixels
a, b, c	coefficients for the quadratic polynomial
$A_{sampled}$	sampled area
A_{weed}	area covered by weeds
h	number of experimental and predicted equations
m, d	slope and intercept of the straight line respectively
M	number of image rows
N	number of crop rows
P_n	centroid (geometric centre) located in the n-th strip, $n = 1,\ldots,12$
$P(i, j)$	points at curved crop rows with (i, j) pixels coordinates
$\hat{P}(i, columns - j + 1)$	translated points from P(i, j), $columns = 2000$
Q	vector of parameters to be estimated
r, g, b	chromatic co-ordinates
R, G, B	RGB (red, green and blue) spectral channels
$R_{max}, G_{max}, B_{max}$	maximum values in the spectral channels
R_n, G_n, B_n	normalised RGB spectral channels
Rs	norm of residues
s	inter-row space in pixels
v	number of experimental and predicted values
(x, y)	upper left corner co-ordinates of the micro-ROI
$(\bar{x}, \bar{y})$	geometric centre of the micro-ROI
(x_c, y_c)	co-ordinates of the centroid
(X_{cross}, Y_{cross})	crossing point defining two rows intersecting
$x_i, \hat{x}_i$	experimental and predicted values at the i-th point, $i = 1,..,v$
Z	vector of measured data

Greek symbols

ε_i (Q, Z)	error between the model (Q) and data (Z) at the i-th equation, $i = 1,..,h$
ρ	distance of the straight line at the origin in polar co-ordinates
θ	angle that forms the normal with the x-axis in polar co-ordinates

1. Introduction

1.1. *Problem statement*

Machine vision systems applied to agricultural tasks have great potential, as explained in Brosnan and Sun (2002) and Davies (2009). The use of technology, including vision systems, in agricultural applications can reduce manual tasks and the cost of crop production (Barreda, Ruíz, & Ribeiro, 2009), and can contribute to the productivity and competitiveness of farmers to ensure agricultural supplies. Moreover, the use of traditional farming methods may lead to indiscriminate use of chemicals (herbicides, fertilisers), increasing production costs, soil depletion and environmental pollution (Astrand & Baerveldt, 2005; Kataoka, Kaneko, Okamoto, & Hata, 2003).

Process automation is gaining an important relevance today. In this regard, crop rows detection in wide row crops is an important issue for both weed identification and automatic guidance. Indeed, plants located inside the inter-row spaces can be considered with very high probability to be weeds, requiring site-specific treatments (Emmi, Gonzalez-de-Soto, Pajares, & Gonzalez-de-Santos, 2014; RHEA, 2014). In autonomous tractors, navigation is mainly based on RTK-GPS (real time kinematics-global positioning system) consisting of two GNSS (global navigation satellite systems) rover antennas providing localisation errors of below ±20 mm (Emmi et al., 2014) for precise guidance. Nevertheless, when small deviations occur with RTK-GPS, crop rows detection is used for precise correction (Kise & Zhang, 2008; Rovira-Más, Zhang, Reid, & Will, 2003). This paper is devoted to automatic crop row detection in maize fields based on a machine vision system.

Outdoor agricultural environments are affected by uncontrolled, variable lighting conditions (sudden shadows, excessive or poor illumination) affecting the image quality. Additionally, different scene conditions can complicate precise crop row detection leading to errors in the estimation of row width from images: a) shortage of crop plants, due to lack of germination, defects during planting or pests/disease; b) high weed density with similar spectral signature to crops close to the crop row; c) different plant heights and volumes, due to different growth stages, are mapped under image perspective projection with different widths; d) curved terrain side slopes, movements of the tractor in irregular terrains, produce the mapping (under perspective projection) of points on the scene into unexpected positions on the image.

In the Andean region of Ecuador, where the present study was carried out, topography is hilly with significant slopes and curved crop rows on terraces are the norm. Terraces are used to avoid soil erosion of agricultural fields caused by natural and artificial irrigation. Curved crop rows also appear in flat parcels of lands with irregular geometry.