Computer-vision guidance extension for inter-row cultivators

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Introduction

Inter-row cultivation is essential to organic producers

- Weed prevention
- Soil aeration

Increase in cultivation as a practice

Mechanical rod sensors are unreliable at early crop stages (< 15 cm)

RTK GPS integration is expensive

Computer-vision is relatively low-cost and has been shown to be viable by research

Objective

To develop a computer-vision extension for existing cultivator guidance systems which meets the following constraints:

Robust → various field and light conditions

Versatile → interfaced with different systems

Low-cost → non-specialized components

System Design

Intel Atom D525, 1.8 GHz, 64GB SSD

Two cameras

- 640x480, scaled to 320x240 (speed)
- 25 FPS max, throttled to 15 FPS
- 24 IR LEDs for low-light illumination
- 1000 mm height at 15º incline (~1 mm/px)

PWM microcontroller with logic level converter (LLC)

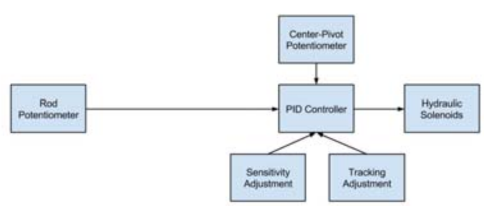
Developed a Python application using OpenCV which runs on an embedded

Testing Equipment

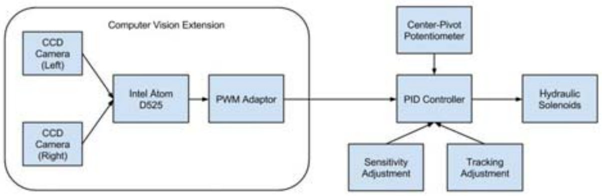
Hiniker 12-row heavy cultivator

Fendt Vario 890

Sukup Auto-Guide hydraulic hitch



Standard Sukup Auto-Guide System



Modified Sukup Auto-Guide with Computer-vision Extension

Calibration

Camera calibration procedure is very simple:

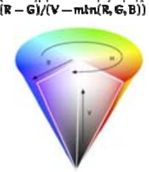
1. Implement is aligned with row*
   1. Distance from row to tools is checked to ensure equidistance
2. Lateral adjustments are made to the camera until row is aligned with center-line of image
3. Vertical adjustments are made to the camera until subject depth from lens to surface is 1000 mm

*Note: any visible line is sufficient

Plant Segmentation - Color Transform

In order to identify the distribution of green plants, the RGB images must be transformed to a de-correlated color-space, in this case via **HSV transformation**

$$H \leftarrow \begin{cases} 60(G-B)/(V-\min(R,G,B)) & \text{if } V=R \\ 120+60(B-R)/(V-\min(R,G,B)) & \text{if } V=G \\ 240+60(R-G)/(V-\min(R,G,B)) & \text{if } V=B \end{cases} \quad S \leftarrow \begin{cases} \frac{V-\min(R,G,B)}{V} & \text{if } V \neq 0 \\ 0 & \text{otherwise} \end{cases} \quad V \leftarrow \max(R,G,B)$$

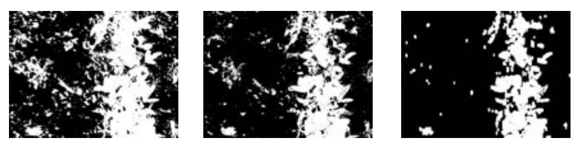


Plant Segmentation - Filtering

A **dynamic band-pass filter** is applied to the HSV image to select for crop colors:

BPPD ← 45 < H < 100, P(50) < S < 255, P(10) < V < P(90)

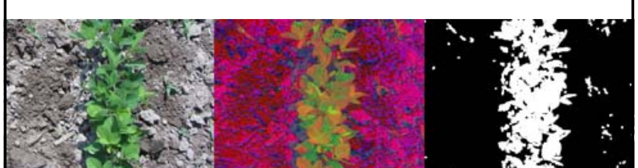
Lastly, **morphological opening** is used to reduce noise on the BPPD matrix



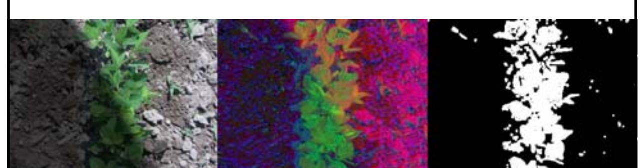
Static band-

Dynamic band-

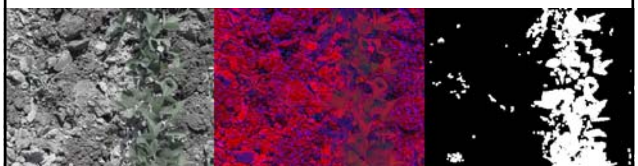
Post-opening



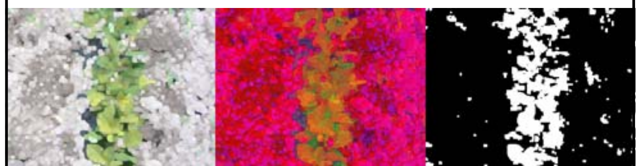
Good



Shadow

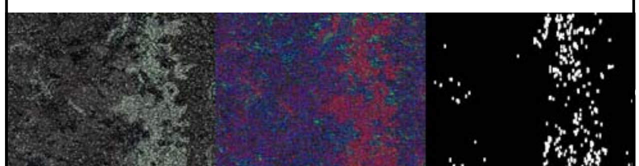


Low saturation



Yellow bias, exposure, and blur

Hyper-exposed (extremely bright day)



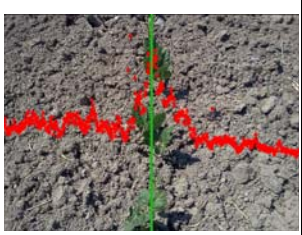
Severe underexposure (night)

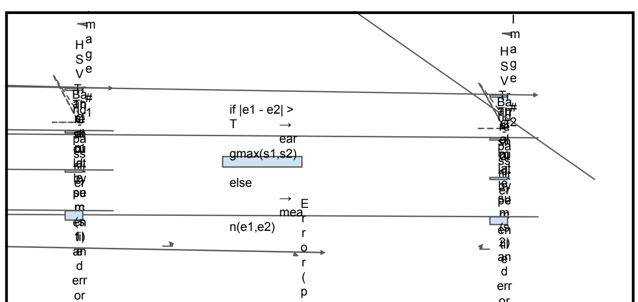
Row Detection

- Offset estimation is achieved with a robust, statistical approach
- Detected plant matter is summed in the **direction of travel** to estimate the row position

  c = sum(BPPD, axis=1)

  i = median([c > percentile(c, 95)])





Flow chart for row detection

Electro-Hydraulic Control

Actuation of the two 32-in stabilizers on the cultivator was conducted via a Proportional-Integral controller.

An 8-bit PWM device integrated with a logic-level converter mapped the signal to the operational range of 0.1 - 8.0 V

```
u = P * e + I * mean(e[-15])
b = limit(u, 0, 255)
v = map(u, 0.1, 8.0)
```

Data Collection

Tested on corn and soybean crops at Agri-Fusion (St-Polycarpe, QC)

Tractor was manually operated → source of random error

Straight drilled fields using StarFire 3000 RTK

Organic cultivars, i.e. no spraying was conducted

Four (4) travel speeds were tested → 6, 8, 10, and 12 km/h

Four (4) crop stages were tested → <10, <15, <20, and >20 cm

Total of 48 trials*

Results

	RMSE (cm)				95th Percentile (cm)			
Treatment	10cm	15cm	20cm	25cm	10cm	15cm	20cm	25cm
Camera	1.70	1.79	1.85	2.17	3.18	3.27	3.23	3.73

MSE / 95th Percentile with respect to crop stage

Results

	RMSE				95th Percentile			
Treatment	6km/h	8km/h	10km/h	12km/h	6km/h	8km/h	10km/h	12km/h
Camera	1.35	2.28	1.75	2.10	2.48	4.13	3.10	3.70

E / 95th Percentile with respect to travel speed

Bonneterre (Phase 2)

After the success with Agri-Fusion, our group was approached by Bonneterre, another large-scale organic producer in Quebec.

Three (3) more systems were built with several design revisions:

Non-angled camera

Fully weather-proof wiring

ABS enclosure

Updated code-base and re-tuned control parameters (SunCo AcuraTrak)

Mounting bracket for camera

Weatherproof Enclosure

- IP65+ connectors
- In-cab display
- On/Off button
- Calibratio

Agri-Vision Mk.II enclosure

In-cab Display

- Minimalistic layout
- Basic operator information:
- Output voltage
- Estimated offset
- Direction of adjustment
- Live video feed
- VESA standard mounting
- 12V DC power

Demo video of Agri-Vision interfaced with the Sunco AcuraTrak

Conclusion

- System has met the stated objectives:
  - Robust
  - Versatile
  - Low-cost
- Computer-vision outperformed mechanical at 10 cm and 15 cm
- Mechanical demonstrated equal performance at 20 cm and out performed computer-vision at >20 cm
- This technology has received significant interest from producers
- A Mk.III model is under development for Sunco (manufacturer of AcuraTrak)

Estimation of tractor ground-speed with SURF keypoint matching

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Introduction

Emerging applications for computer-vision on agricultural implements

- Row-crop cultivation
- Strip tillage
- Post-harvest spraying

Motion feedback is very useful for such applications

- Orientation
- Responsiveness

Incorporating speed detection into these systems can be problematic

- RTK GPS can be expensive

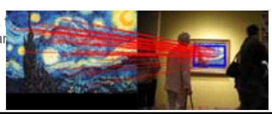
Keypoint Matching

Keypoint matching is the process of extracting feature descriptors from multiple images and determining consistent pairs (e.g. via knn-Matching)

Several mathematical algorithms exist for producing keypoints

- SIFT
- SURF
- ORB

ORB and SURF are >3x
SURF is very good at har



Objective

Evaluate the effectiveness of a computer-vision system for estimating ground speed of an agricultural vehicle using the SURF algorithm with a single, low resolution camera.

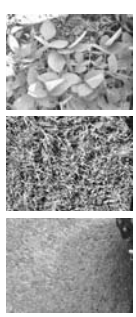
Data Collection

Six (6) surface types

- Pavement
- Gravel
- Soil / Residue
- Turf Grass
- Hay Grass
- Mature Soy

For each surface type, five (5) videos were collected

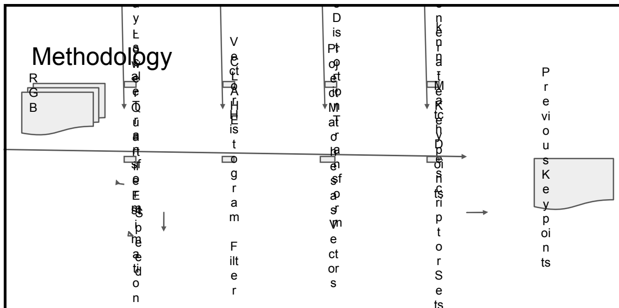
0 km/h to 18 km/h to 0 km/h in ~45 seconds



Data Collection

- John Deere Gator 850D
- Trials conducted in high gear
- 640 by 480 px CMOS camera
- 1000 mm above surface
- 25 frames-per-second
- Coverage height measured

Methodology



Process diagram for Local Vector Estimation (LVE).

Methodology

Two consecutive RGB images, 12.8 km/h

Pre-Processing I - Gray-scale Transform

Firstly, the input image must be converted from RGB to gray-scale

$$Y \leftarrow 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B$$

R
G

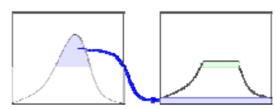
G
r

Pre-Processing II - CLAHE

The contrast of gray-scale images is improved with contrast limited adaptive histogram equalization (CLAHE)

Prevents over-amplification of noise compared to standard histogram equalization

Clips histograms of image subsets (redistributing values equally among bins) before computing the cumulative distribution function (CDF)



Pre-Processing III - Lens Distortion

Lens distortion can be corrected using a matrix transformation

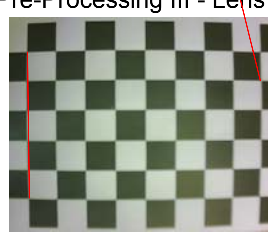
With a checkerboard image we can locate corners (30mm x 30 mm)

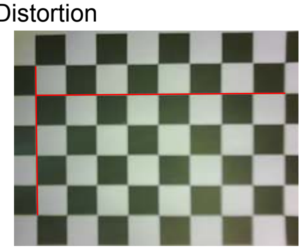
Camera calibration parameters found by rectilinearizing the set of points

$$Distortion_{coefficients} = (k_1 \quad k_2 \quad p_1 \quad p_2 \quad k_3)$$

$$x_{corrected} = x + [2p_1xy + p_2(r^2 + 2x^2)]$$
$$y_{corrected} = y + [p_1(r^2 + 2y^2) + 2p_2xy]$$

Pre-Processing III - Lens Distortion





Lens distortion correction with checkerboard pattern.

Pre-Processing IV - Summary

Input image (left) and corrected output image (right)

SURF - Speeded Up Robust Features

SURF is a keypoint detection algorithm which works by iteratively applying gaussian filters and selecting points which exceed a Hessian threshold.

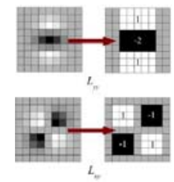
Wavelet responses in the horizontal and vertical directions produce a 128-dim array of feature descriptors for each keypoint.

For this project, the recommended SURF parameters were used:

Hessian threshold = 1000

Gaussian octaves = 4

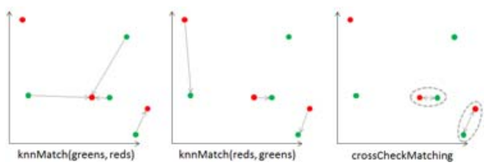
Gaussian octave layers = 2



Keypoint Matching

Brute force knn-Matching (N=2) is used find keypoint pairs between two consecutive images

Cross-checking is utilized to produce only high-quality pairs



Calculating Vectors

Each keypoint pair is converted from x-y to polar:

vx = x2- x1

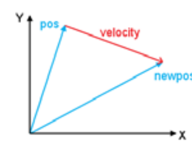
vy = y2- y1

r = sqrt(vx2+vy2)

ϕ = atan2(vx, vy)

A frame-rate of 25.0 Hz is assumed and 1.0 mm/px is converted to kilometers:

||v|| = 3600 · r / 25.0



Vector Filtering

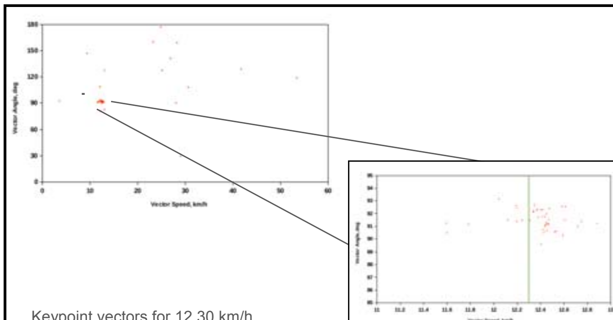
Need to reject improper vectors, i.e. those caused by shadows / fixed objects

Select for the largest set of vectors traveling in the same direction

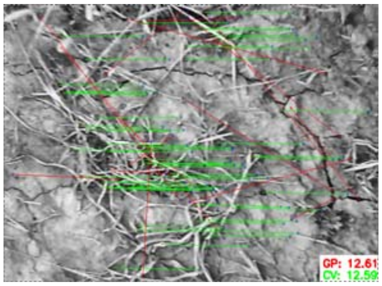
Compute the 25th percentile of vector speeds within that subset

Compensates for error caused by subject distance

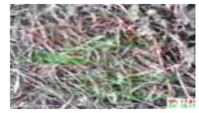
Computationally simple and produces consistent results



Keypoint vectors for 12.30 km/h



Graphical representation of keypoint matching with vector highlighting of good (green) and rejected (red) pairs



Video demonstration of keypoint matching

Results

Surface	RMSE (km/h)	Slope (km/km)	Offset (km/h)
Asphalt (0 cm)	0.221	1.001	0.046
Gravel (< 2.5 cm)	0.258	0.994	-0.097
Residue (2.5 - 10 cm)	0.249	1.006	-0.175
Turf Grass (10 - 15 cm)	0.572	1.056	-0.160
Hay Grass (15 – 20 cm)	0.858	1.069	-0.054

Table 1. Average RMSE and linear regression values.

Results

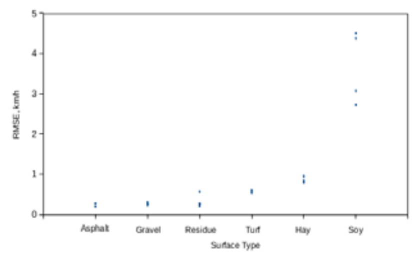


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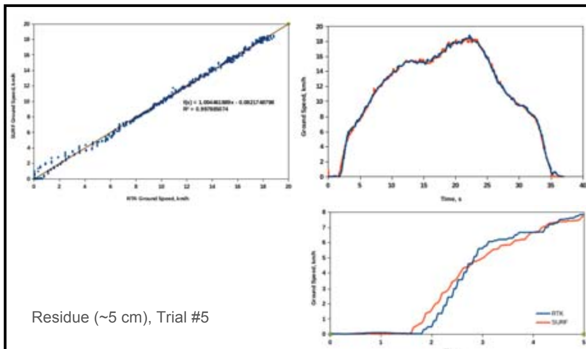
Figure 1. RMSE of trials by surface type.



Residue (~5 cm), Trial #5

Conclusions

Sufficient accuracy in the operational range of most agricultural implements (0 km/h to 12 km/h)

Noticeably different behavior than RTK during acceleration

SURF algorithm was capable of 2 - 6 Hz

Accuracy degrades with surface depth variability, solved by sensor fusion:

Stereo-vision

Time-of-flight / LIDAR

Ultrasonic

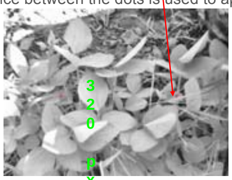
Laser-point matching

Further Research - Laser-point Matching

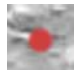
Two laser pointers are directed to the surface, parallel to camera

Keypoint matching is used to identify the laser dots

Distance between the dots is used to approximate subject depth



400 px



Further Research - ORB vs. SURF

SURF	ORB
Patent protected	Opensource
Only capable of 2 - 6 Hz	Theoretically faster than SURF
Great matching with blurring	Poor matching with blurring

Research Question (Part II): Which keypoint matching algorithm is best-suited for real-time ground speed estimation, SURF or ORB?

Questions?

A QUICK-INSTALL TRACTOR GUIDANCE SYSTEM RELYING ON COMPUTER VISION

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McGill

PROJECT OBJECTIVE

- To design a camera-based automated guidance system capable of guiding an unladen agricultural tractor within a desired path (crop row) at speeds between 1 m/s and the maximum practical operating speed for the tractor (5 m/s).
- The system also has to meet the following requirements:
  - Not restricted to a specific crop or task
  - Compatibility with all agricultural vehicles equipped with power steering
  - Easy to install within minutes
  - Inexpensive

DESIGN REQUIREMENTS

Plant Segmentation

- RGB images must be filtered to distinguish plant matter from soil
- Capability to handle different crops (e.g. soybeans, corn)

Row Detection

- The crop row must be determined after plants have been identified
- Capability to handle high weed density and inconsistent rows

Ground Speed Measurement

- Enough keypoints must be matched to measure progression between frames
- Capability to handle poor lighting (e.g. shadows)

Vehicle Control

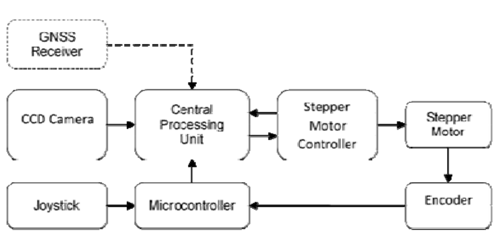
- The guidance adjustments must be smooth and not exhibit hunting oscillations
- Capability to handle rows with 5 cm error

SYSTEM COMPONENTS

- Rugged Camera
- Onboard vehicle computer
- Stepper motor, encoder and mounting hardware
- Joystick and dedicated microcontroller
- HSI band-pass plant detection algorithm
- SURF ground speed estimation
- RTK-level GNSS receiver (for performance evaluation)

Camera, onboard computer, steering wheel hub adapter, and joystick.

SYSTEM DIAGRAM



Steering system diagram.

CAMERA IMPLEMENTATION

(a) (b)

One meter above garden hose on tarmac (a), and above soybeans with the GPS antenna (b)

PLANT SEGMENTATION

- A HSI Band-Pass Plant Detection algorithm (BPPD) was developed to address false-negative and false-positive plant identification in non-diffuse lighting.

$$H_{ij} = \begin{cases} 60 \cdot \left(\frac{G_{ij} - B_{ij}}{I_{ij} - min(R_{ij}, G_{ij}, B_{ij})} \right) & if\ I_{ij} = R_{ij} \\ 120 + 60 \cdot \left(\frac{B_{ij} - R_{ij}}{I_{ij} - min(R_{ij}, G_{ij}, B_{ij})} \right) & if\ I_{ij} = G_{ij} \\ 240 + 60 \cdot \left(\frac{R_{ij} - G_{ij}}{I_{ij} - min(R_{ij}, G_{ij}, B_{ij})} \right) & if\ I_{ij} = B_{ij} \end{cases}$$

$$S_{ij} = \begin{cases} 0 & if\ I_{ij} = 0 \\ \frac{I_{ij} - min(R_{ij}, G_{ij}, B_{ij})}{I_{ij}} & if\ I_{ij} \neq 0 \end{cases}$$

$$I_{ij} = \max(R_{ij}, G_{ij}, B_{ij})$$

$$BPPD_{ij} = \begin{cases} 1 & if\ H_{ij} > H_{min} \wedge H_{ij} < H_{max} \wedge S_{ij} > mean(S) \wedge I_{ij} > mean(I) \\ 0 & otherwise \end{cases}$$

HSI SEGMENTATION ALGORITHM

(a) (b)

Original (a) compared to improved HSI filter (b)

CROP ROW DETECTION

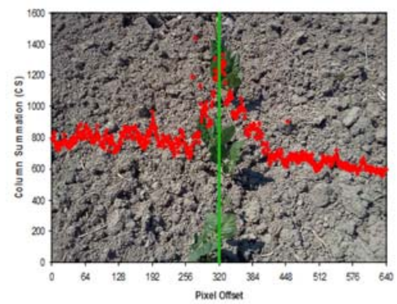
- A statistical band-pass filter for estimating lateral crop offset was developed based on work by Slaughter et al. (1996) and Brivot et al. (1997)

$$CS_i = \sum_{j=0}^{n_j} BPPD_{ij}$$

$$CI_i = \begin{cases} i & if\ CS_i \geq mean(CS) + 2 \cdot std(CS) \\ N/A & if\ CS_i < mean(CS) + 2 \cdot std(CS) \end{cases}$$

$$Offset = \begin{cases} median(CI) - \frac{n}{2} & if\ count(CI) > 0 \\ i_{max\ (CS)} - \frac{n_i}{2} & if\ count(CI) = 0 \end{cases}$$

ROW DETECTION DEMONSTRATION

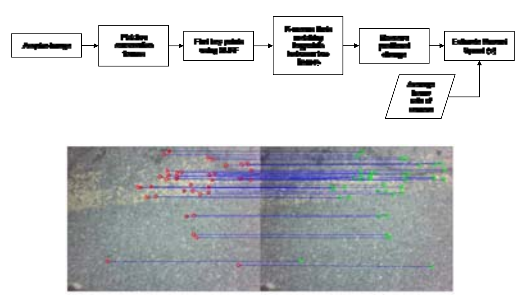


Stanhope et al. 2014

GROUND SPEED MEASUREMENT

- Using two consecutive frames of the video stream to identify keypoints using SURF algorithm (Bay et al. 2006)
- K-means nearest neighbor matching finds matching keypoints
- Average velocity calculated by determining positional change multiplied by average frame rate of camera (Stanhope, 2015)

GROUND SPEED MEASUREMENT



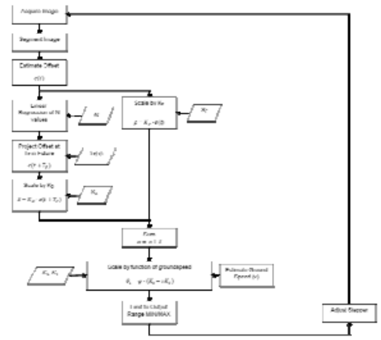
Simplified ground speed estimation flowchart and illustration.

VEHICLE CONTROL

- T5050 New Holland tractor steered by stepper motor and steering wheel hub adapter attached to front window using suction cups
- PD feedback controller design

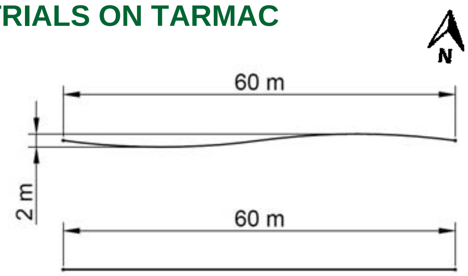
Steering apparatus mounted to the front window of the tractor.

VEHICLE CONTROL ALGORITHM



Simplified control algorithm flowchart.

TRIALS ON TARMAC

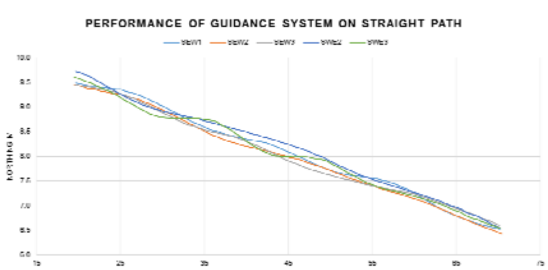


Arrangement of the two test layouts for the garden hose, on tarmac.

TRIALS ON TARMAC AT 2.5 M/S

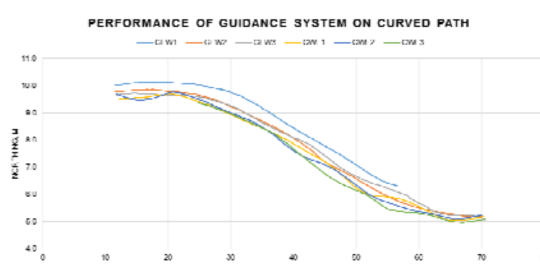
Trajectory	Direction of Travel	Trial	Number of Records	Mean Absolute Error (cm)	RMSE (cm)	95th Percentile (cm)
Straight	East-West	1	110	4.8	6.1	12.5
		2	110	5.9	7.1	13.7
		3	109	7.8	9.6	17.4
	West-East	1	111	10.9	12.5	20.9
		2	112	2.3	2.6	4.4
	Overall		552	6.9	8.6	16.7
Curved	East-West	1	98	15.2	16.4	27.5
		2	127	4.1	5.0	8.9
		3	129	4.6	5.7	10.6
	West-East	1	128	9.1	11.3	20.4
		2	129	9.8	11.8	19.6
		3	98	13.6	14.9	22.0
	Overall		709	9.2	11.3	20.6

RTK TRACKING



Tracking of the test tractor as recorded by GPS, in relation to arbitrarily chosen reference point.

RTK TRACKING CONT'D



Tracking of the test tractor as recorded by GPS, in relation to arbitrarily chosen reference point.

WORK IN PROGRESS

- Higher operating speeds (5 m/s)
- Kalman Filter
- Operator Assisted Reinforcement Learning

  →Q-Learning

Authors next to test tractor.

Q-LEARNING

- Model-free reinforcement learning technique
- The algorithm can be written:
  1. Obtain the current state s_t.
  2. Choose a decision d_t and execute it.
  3. Obtain the new state s_{t+1} and the immediate reward r.
  4. Update the matrix $Q(s_t, d_t)$ with the equation:
     $$Q(s_t, d_t) = (1-\alpha)\cdot Q(s_t, d_t) + \alpha\cdot\left(r + \gamma\cdot \max_{d_{t+1}} Q(s_{t+1}, d_{t+1})\right)$$
  5. Assign $s_t = s_{t+1}$
  6. While $s_t \neq s_{optimal}$ return to 2.

  where α and γ are the learning rate and the discount factor, respectively.

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