

Tactile Sensing & Visually-Impaired Navigation in Densely Planted Row Crops, for Precision Fertilization by Small UGVs

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ABSTRACT

Navigating outdoor agricultural environments with cameras or ranging sensors is challenging due to sensor occlusion, lighting variability, and dense vegetation, particularly in tightly-spaced row crops. These environments present visually similar surfaces, making it difficult for vision-based systems to distinguish between rigid obstacles and flexible, traversable objects like weeds. As plant density increases, the margin of error narrows, limiting the effectiveness of traditional visual sensing. To overcome these challenges, we present a novel tactile-based perception system for autonomous navigation without any form of remote sensing. The system uses a mechanical feeler with rotary encoders to detect and map rigid obstacles, such as corn stalks, while filtering out flexible features like leaves and weeds. Through real-time classification of sensor deflections, the system achieves approximately 97 % accuracy in detecting obstacles and global positioning accuracy within 4 cm of a plant's true location. The tactile sensor system, alongside blind-adapted path-planning (A*) and path-following (pure pursuit) algorithms, further allow an unmanned ground vehicle to autonomously navigate cornfields. Prototype sensors and the navigation method were tested in simulation, a controlled real-world environment, and a mature, unmanicured cornfield, demonstrating autonomous capabilities of > 100 m in simulated and > 30 m in real-world cornfields, prior to needing intervention. The tactile system overcomes row curvature, planting gaps, dense weeds, and canopy variability—without relying on vision or ranging sensors. With additional refinement, visual and tactile sensing modalities may be combined for more reliable obstacle detection and navigation for small robots operating in visually-occluded agricultural environments.

1. Introduction

In perennial cropping (e.g., apple orchards, vineyards, berry farms, etc.), precision agriculture (PA) commonly involves the use of permanent sensor networks to manage crop development in-season, as static systems for monitoring and resource delivery can be placed in the environment indefinitely. However, applying these static systems to row crops—such as corn, wheat, and sorghum—is challenging due to the dynamic nature of these fields, with plants growing nearly a meter in weeks; inter-row (63.5–76.2 cm) and intra-row (10–24 cm) plant spacing imposes limitations on the types of systems that can be installed. As environmental concerns increase and profit margins narrow, innovative solutions to enhance the efficiency of row-cropping are needed. Autonomous agricultural field operations are well studied, and the technical feasibility of using automated systems for various crops, tasks and abilities has been shown (e.g., Bechar & Vigneault, 2016; Bechar & Vigneault, 2017; Shamshiri et al., 2018; Fountas et al., 2020), but the

crops most commonly researched are cultivated in predictable, organized, and mostly unchanging environments like greenhouses (e.g., Belforte et al., 2006; Rapado-Rincón et al., 2023; van Herck et al., 2020; Barth et al., 2016) or in orchards (e.g., Bergerman et al., 2015; Bloch et al., 2018; Opiyo et al., 2021). Agricultural environments that are increasingly cluttered and dynamic, like broadleaf row-crop fields, are less developed in terms of automation, limiting the extent precision practices can be applied to enhance productivity there.

Fig. 1 shows a taxonomy of design considerations for automated PA systems. System form implicitly reflects designated requirements; functional elements characterize objectives of the precision task, while the operational elements characterize the modes of operation and strategies employed to complete those objectives. Conversely, assuming a system form fixes other elements of a PA system, constraining the techniques that can be employed to manage crop development. Row-crop agriculture naturally lends itself toward involvement of vehicles to provide temporary, mobile precision in lieu of more permanent solutions, so many row-crop PA technologies are additive to conventional

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Nomenclature		Symbols	
ADF	Acid detergent fiber	B	Area occupied by vehicle footprint
aNDF	Neutral detergent fiber using amylase	$\beta(s)$	Vehicle heading
CP	Crude protein	D	Directed graph
C/N0	Carrier-to-noise power spectral density	d	Perpendicular obstacle incidence length
DOP	Dilution of precision	e, E	Edges in graph
DM	Dry matter	F	Sensor frame
EKF	Extended Kalman Filter	f_{kin}	Kinematic constraint
GDD	Growing degree days	$f(n)$	A* evaluation function
GNSS	Global navigation satellite system	G	Global frame
HFF	High-frequency N fertilization	$g(n)$	A* cost-to-come
HDOP	Horizontal dilution of precision	$h(n)$	A* heuristic cost
N	Nitrogen	J	Cost to be minimized during navigation
NBR	Nitrogen base rate	k	Timestep
NEL	Net-energy for lactation	L	Vehicle wheelbase
NEm	Net-energy for maintenance	l	Obstacle incidence length along sensor paddle
NEg	Net-energy for gain	M	Vehicle frame
NFC	Non-fiber carbohydrates	n	Node
NMEA	National Marine Electronics Association	$o(n)$	A* obstacle penalty
PA	Precision agriculture	P_{obs}	Area occupied by obstacles
PDOP	Position (3D) dilution of precision	$\hat{P}$	Estimated map of environment
ROS	Robot operating system	$\hat{P}_{i,k}$	Individual plant in map
RTCM	Radio Technical Commission for Maritime Services	p	Obstacle deflection length along vehicle
RTK	Real-time kinematic	S_k	Sensor contact state
R1, R2, R3, ...	Reproductive growth stages	S	Directed path
SDI	Surface drip irrigation	s_{max}	Max path length
SSDI	Sub-surface drip irrigation	T	Contact state transition function
SV	Space vehicle, satellite	θ	Feeler sensor state vector
TDN	Total digestible nutrients	$u_r(s)$	Control inputs along the path
UAN	Urea ammonium nitrate	v	Vehicle forward velocity
V1, V2, V3...	Vegetative growth stages	v, V	Vertices in graph
VDOP	Vertical dilution of precision	w_i	Goal points
		$\hat{x}$	Estimated vehicle speed in G
		$x_r(s)$	Vehicle state (global position, heading)

tractor systems (e.g., variable rate technologies). These systems, however, cannot provide precision *in-season*, because they lack the ground clearance needed to traverse fields without damaging the crop. UAVs can fly above the crop canopy and are already used to complete a variety of assessment tasks, but they lack versatility, cannot precisely deliver material, and cannot work in close proximity to plants. High clearance

vehicles can operate above the canopy, but they impart substantial pressure on the ground, inducing anthropogenic soil compaction and disrupting normal operations (Horn et al., 1995).

We start instead by defining system requirements of an automated row-crop PA system, then consider candidate solutions that enable in-season PA in row-cropping. The **functional requirements** might assert

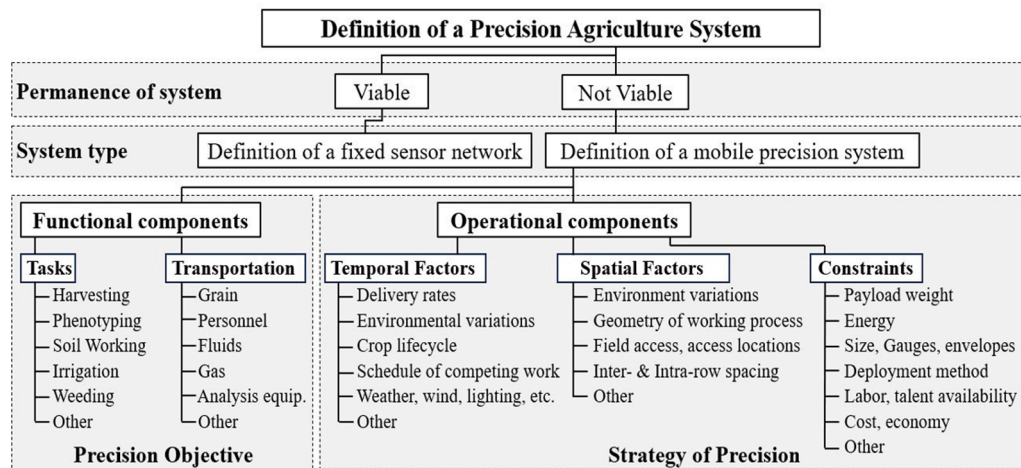


Fig. 1. Definition of Components for a Precision Agriculture System. The vehicles selected to perform a precision task have constraints which dictate the operational and functional aspects of the overall system.

that the system: **a.)** Autonomously responds to the crop and environment and embodies multifunctionality (tasks performed). **b.)** Reliably moves material and equipment to and from the environment absent personnel (transportation). The PA system might also have **operational requirements** stating it must: **a.)** Complete tasks under time-sensitive schedules, in the presence of varying environmental factors like weather and lighting, across the entire development cycle of the crop (temporal factors). **b.)** Be robust to rapid plant growth dynamics, varying terrain, and tightly packed, narrow rows (spatial factors). **c.)** Be impermanent, energy efficient, serviceable, affordable, easy-to-deploy, and sized to minimize crop and environment damage (constraining elements). Starting with this framework, it is easy to conceptualize a variety of yield-enhancing techniques, and then select and engineer transportation mechanisms to achieve the PA task.

In particular, [Section 2](#) discusses high-frequency applications of nitrogen (N) fertilizer to enhance yield in corn, a strategy impossible for conventional tractors but well-suited for small UGVs travelling down individual rows. We show through parametric modelling that light-weight UGVs can effectively overcome individual payload limitations to deliver the requisite N at scale, while satisfying the designated requirements. However, to autonomously manage tasks like fertilization under-the-canopy, robust sensing and navigation is crucial. [Section 3](#) considers comparably sized vehicles and the techniques others have utilized to navigate the harsh environment, highlighting the challenges of visual sensing in row crops, specifically occlusion. Additional background is included on overcoming visual-impairment through tactile-visual sensory inputs. [Section 4](#) introduces a novel tactile-only system to map plant stalks, including the comprising passive sensors, the obstacle detection algorithm, and the identification of obstacle positions using real-time sensor data. We then show in [Section 5](#) that the positioning information obtained through tactile means is sufficient to navigate entirely blind or at night, using modified common path-planning and path-following algorithms. Results of simulated and real-world robot navigation are presented in [Sections 6 and 7](#), respectively, and conclusions on tactile sensing are presented in [Section 8](#). Via the proposed approach, UGV navigation in row crops can be made more robust, and new, efficient PA methods can be adopted.

2. Motivation

Corn, the prototypical broadleaf row crop, is planted on ~ 94 M acres in the U.S. ([USDA-NASS, 2023](#)) and its production consumes significant resources, including > 230 T liters of water and > 6.1 M tons of N fertilizer annually ([USDA-NASS, 2021](#)). Crop maturity is characterized by vegetative stages, identified by counting the number of collared leaves after emergence ([Ritchie & Hanway, 1982](#)), and reproductive stages, based on the appearance of the uppermost ear and grain characteristics like moisture content. Typically, fertilizer is applied before planting based on soil tests. *In situ*, soil N undergoes microbial-induced mineralization into nitrates (NO_3^-), the form largely used by corn. NO_3^- is highly susceptible to loss via leaching and denitrification. Depending on the application method, up to 50 % of applied N may be unused by the crop, causing environmental loss and financial strain for growers. Corn N-uptake follows a sigmoidal-shaped curve as in [Fig. 2](#) ([Abendroth et al., 2011](#); [Boyer, 2013](#)). Similar relationships exist for above ground dry matter accumulation and other nutrients ([Boyer, 2013](#)). Between VE (emergence) and V9, growth for most of corn's constituent structures is initiated, but little nutrient uptake occurs during this window. At V6, nutrient uptake increases substantially and remains approximately linear for several weeks, typically until VT (tasseling). By VT, as much as 50 % of macronutrient uptake is yet to occur. Temporal synchrony between N supply and demand largely affects stress levels, yield, and loss, but most farms apply N fertilizer before the crop can efficiently assimilate N, generally prior to V6 ([Venterea & Coulter, 2015](#)). Delayed single-rate N applications can induce early season stress, but applications have successfully been delayed to V16 with little to no irreversible

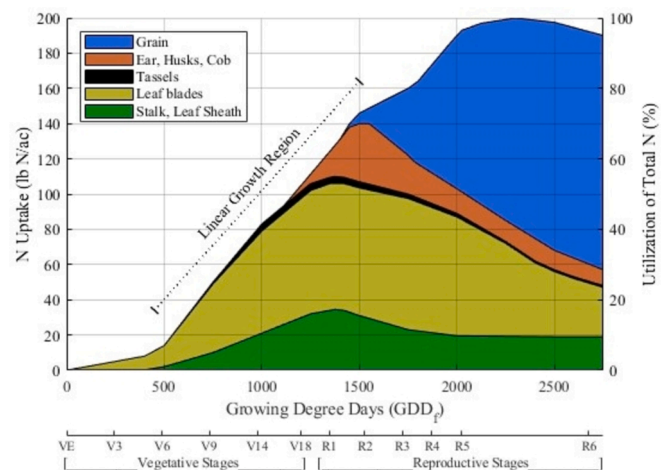


Fig. 2. Corn Nitrogen Uptake. Cumulative N uptake by corn is known to follow an S-shaped curve, in terms of growing degree days, “GDDs”, and corn stage (adapted from [Abendroth et al. 2011](#); [Boyer, 2013](#)).

yield loss, even if plants show severe stress-related symptoms; excellent yields have been achieved with rescue N applied V6-VT ([Scharf et al., 2002](#); [Jung et al., 1972](#); [Nelson et al., 2011](#); [Binder et al., 2000](#)).

2.1. High-frequency fertilization

N delivery over a larger, seasonal split schedule (i.e., spoon-feeding the crop slowly over time), has been identified as an effective practice in reducing stress, truncating N loss and enhancing yield ([Borzaco et al., 2013](#); [Venterea and Coulter, 2015](#); [Ogle et al., 2014](#); [Ribaud et al., 2011](#)), but experimental work is limited and presents mixed results. [Davies et al. \(2020\)](#) observed that three-way split high frequency N fertilization (HFF) in corn can enhance yield by 20–210 % across N rates and maintain yield with 40 % less fertilizer. [Lu et al. \(2021\)](#) compared a standard upfront broadcast N rate to various split N applications supplied through surface drip irrigation (SDI) lines, revealing that four-way split HFF maintained higher soil NO_3^- levels and resulted in elevated biomass and grain yield. Even at a reduced N-rate, four-way HFF increased N use efficiency by up to 143.4 % compared to conventional practices. In corn, daily fertigation via SDI or subsurface drip irrigation (SSDI) lines represents the extreme of HFF. Grain yield, dry matter accumulation, plant height, and water and N use efficiency all appear to improve as a producer approaches daily fertigation ([Chauhdary et al., 2019](#)). However, SDI and SSDI is impractical for corn at scale.

2.2. Phenotypic response experiment to HFF

In 2022, we performed our own experiment to investigate HFF in corn further. The study, a 2^4 full factorial, randomized block experiment, compared the **spread of UAN delivery** (surface-band on the row or uniformly surface broadcast), **total N amount** (80 % of an N-base-rate, “NBR”, as determined by grid sampling for existing soil nutrients, or 100 % NBR), **“effort” of the schedule** (N-schedule unweighted or weighted to plant uptake), and **fertilization frequency** (early season or 5-way HFF). All 16 treatments were tested across two replications on a 99-day flex ear silage hybrid (RT49T61), on a total area of ~ 1.26 ac. in New Hampshire. N schedules were engineered against the uptake curve in [Fig. 2](#), scaled temporally to reflect a 99-day hybrid, and normalized against the total designated N amount as the assumed N uptake amount. The timing of applications reflected crop developmental stages. For single N-rate applications, delivery was scheduled at V3. For 2-way split applications, the intended schedule was 40 % of the N rate at V3 and 60 % of the N rate at V9. For 5-way HFF weighted to plant uptake, the intended schedule was 9.9 % of the N rate at V3, 18.4 % at V6, 26.7 % at

V9, 26.7 % at V11, and 18.4 % shortly after tasseling. Unweighted, 5-way HFF was set to occur at the same times at a static 20 % of the prescribed N rate. An example HFF plan is shown in Fig. 3, which indicates the weight (in g N) to apply at each window. N (in the form of UAN-32) was delivered using a commercial backpack sprayer via the designated application method. Across the season, 160 forage samples were gathered and analyzed by Dairy One Forage Laboratory in Ithaca, NY for dry matter (DM) composition, % crude protein (CP, total protein-bound N), % acid detergent fiber (ADF), % neutral detergent fiber using amylase (aNDF), % non-fiber carbohydrates (NFC), % total digestible nutrients (TDN), net energy for lactation (NEL), net energy for maintenance (NEm), net energy for gain (NEg), % starch, % nitrate, and nitrate ppm in DM. The number of kernel rows and kernels per row were estimated for treatments through representative sampling. Crop development was tracked by measuring stalk heights, counting collared leaves, and recording growing degree days (GDDs). Finally, silage yield at harvest (~68 % moisture content) was estimated by harvesting and weighing ~ 0.001 ac. from each treatment block.

Significant results ($P < 0.1$) are summarized here. N-amount and N-placement had little effect on any of the response variables across treatments, but HFF and weighted treatment schedules lead to significant benefits over to conventional fertilization. The best performing treatment in both replications received 80 % NBR through 5-way HFF weighted to plant uptake via uniform broadcast. The worst performing treatments received either 80 % NBR applied uniformly in 2-way split or 100 % NBR applied all-at-once on-the-row. Silage yield estimates are compared between factor levels in Table 1. Silage yield differences were small between delivery methods and N-rates, but treatments weighted to corn N-uptake had higher silage yield than treatments unweighted to plant uptake in both replications, corresponding to a 0.9 % benefit in Rep1, a 12.8 % benefit in Rep2, and a 6.1 % benefit overall; treatments distributed in time (5-way HFF) performed better than upfront treatments – 6.2 % better in Rep1, 10.6 % in Rep2, and 8.2 % overall. Phenotypic results were similar. Schedules weighted to plant uptake had approximately 3.5 % more kernels than simple schedules applied at fixed rates ($P = 0.1$). N treatments weighted to plant uptake also had significantly higher DM % CP ($P = 0.026$), % TDN ($P = 0.097$), and % starch ($P = 0.099$), plus higher energy metrics than fixed-rate schedules. Similarly, HFF resulted in significantly more ($P = 0.003$) kernels per row and kernels overall ($P = 0.006$) than conventional schedules. These results indicate that 5-way HFF may lead to a higher transition of florets (i.

e., potential kernels) into kernels. 5-way HFF also resulted in significantly higher DM % CP ($P = 0.097$), % TDN ($P = 0.071$), % starch ($P = 0.016$), and % NFC ($P = 0.073$), in addition to significantly higher NEL ($P = 0.097$) and NEm ($P = 0.096$) compared with early season applications. Direct evidence is still needed regarding grain yield, but the silage resulting from HFF was heavier and significantly more protein-rich, starchy, and energy-dense than early season schedules. Schedules weighted to plant uptake are also promising. Early evidence suggests spoon-feeding N to corn slowly over time is a compelling strategy to reduce N losses and enhance crop yield. With enhanced automation, small robotic equipment can make strategies like these possible at scale.

2.3. Model of UGV Forms for fertilization

For an average-sized U.S. farm (445 ac) producing corn and applying 150 lb. of N fertilizer per acre in the form of UAN-32, the total load comprises ~ 210,000 lb. (19,000 gallons) of material. Conventionally, N fertilizer is delivered all-at-once at the beginning of a cropping season, using a self-propelled or towed sprayer, for example, with a 1,600-gallon tank and a 30-row boom span. The equipment requires a producer to fill the fertilizer tank 12–13 times and the vehicle to travel ~ 50 total miles, all while the 40,000 lb. (fully loaded) machine compacts the soil. By contrast, applying the same amount of UAN gradually over time by increasing the number of plant visitation and proportionally decreasing the N rate per application, can be done by a system of smaller vehicles working collaboratively. Fig. 4 shows parametric relationships between mass, distance, and average speed as a function of the number of robots in a distributed fertilizer system. With each vehicle fertilizing two rows simultaneously (travelling down one row alley), fertilization of an average farm could, for example, be completed by 40 vehicles, each refilling a 7.5-gallon tank 63 times during the season. Each plant is visited five times, and each robot travels ~ 92 miles over the season. Given eight weeks to complete the task and assuming 50 % downtime of vehicles for charging and weather-related delays requires each vehicle to travel at a nominal speed of only ~ 0.14 mph (6 cm/s), well within the range of possibility for an automated robot in a cluttered environment.

As robot mass decreases, the number of robots required to service the farm increases, and the total travel distance and nominal speed of each robot decreases. The number of plant visits viable per season increases as land area decreases. A 350-acre farm (near the average size in Iowa or Illinois) could increase fertilization frequency to seven. A 175-acre farm (average in Vermont, Ohio, Maine) could increase fertilization frequency to 14, visiting each plant every 4 days, or that farm could use fewer robots to maintain five visitations per season. Based on prior robot terramechanics and design for deformable terrain (Ray et al., 2007; Ray, 2009; Lever et al., 2012; Arcone et al., 2016; Lines et al., 2021, 2023) and assuming 20 % terrain resistance, a reasonable energy consumption rate for a carefully designed 45 kg robot with 45 kg payload capacity is ~ 20 m/Wh. This onboard energy requirement permits solar recharging of batteries. For typical row spacing, ~2.7 km of travel is needed to cover one acre while fertilizing two rows at a time. One small robot can carry fertilizer for 1–2 acres at a time, can cover ~ 3–4 acres prior to needing to recharge, and can do so in ~ 5–6 h. In short, HFF is viable for small-medium sized farms using UGVs. The lengthy travel distances required of these vehicles is presently a limitation with respect to robustness of navigation frameworks, and these frameworks are addressed in subsequent sections.

3. Background

3.1. Visual Applicators, Robots, and Ag-UGVs

Similarly sized in-row and under-the-canopy UGVs have been developed for phenotyping, scouting, sowing cover crops, and stalk penetrometry in crops like corn and sorghum, but navigation performance is limited. Notable examples include AgTracker and its precursor

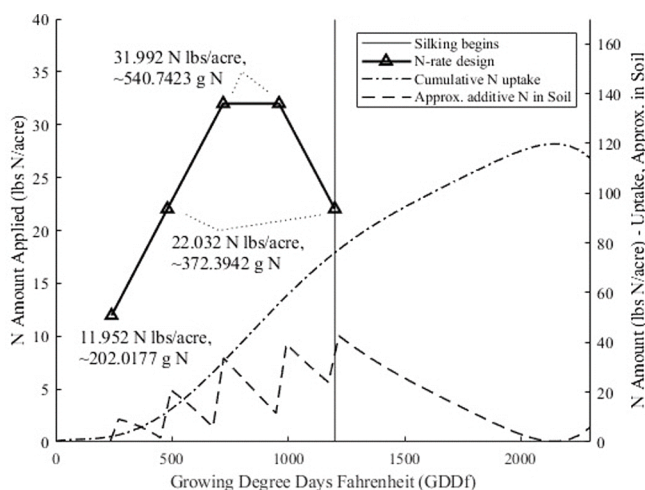
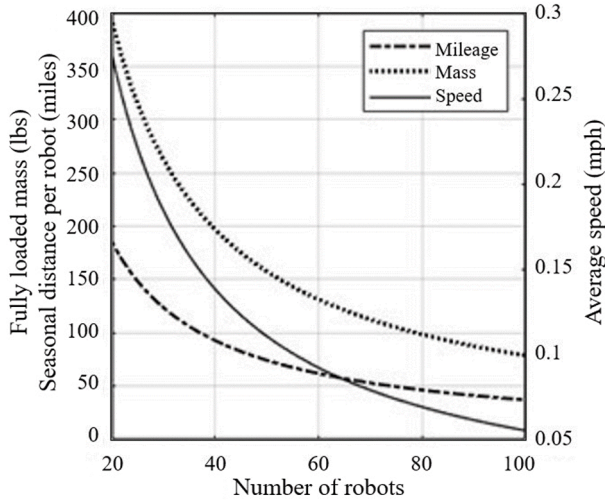


Fig. 3. Example Treatment for High-Frequency N Fertilization. Presented is an example high-frequency N fertilization schedule as applied in the crop response study. The approximate amount of N in soil that remains available for assimilation, assuming no environmental loss, is plotted for reference as a function of GDD₅₀.

Table 1

Silage Yield (tn/ac) Assessment by two-sample t-Tests.

	Rep1 (n = 8 √ level)			Rep2 (n = 8 √ level)			Rep1 + Rep2 (n = 16 √ level)		
	$\bar{x}$	s^2	P	$\bar{x}$	s^2	P	$\bar{x}$	s^2	P
Broadcast	34.27	11.16	0.35	28.95	15.44	0.30	31.61	19.97	0.30
On-Row	33.75	3.57		27.80	20.35		30.78	20.61	
100 % NBR	34.65	3.55	0.18	26.80	16.69	0.07	30.73	25.87	0.28
80 % NBR	33.37	10.41		29.95	14.21		31.66	14.62	
Weighted	34.16	9.31	0.42	30.08	18.96	0.05	32.12	17.63	0.12
Unweighted	33.86	5.53		26.67	10.95		30.27	21.49	
5-way HFF	35.04	6.51	0.06	29.80	12.77	0.09	32.42	16.33	0.06
Conventional	32.98	5.96		26.95	19.15		29.97	21.41	


Fig. 4. UGV Model of Distributed Fertilization. The parametric model shows that fertilization could be performed by a collaborative network of UGVs.

(Grift et al., 2005), Robotanist (Mueller-Sim et al., 2017), Phenobot 3.0 (Tuel, 2019; Xiang et al., 2023; Gai et al., 2021), Vinobot (Shafiekhani et al., 2017), TerraSentia and TERRA-MEPP (Young et al., 2018; Higuti et al., 2018; Velasquez et al., 2022), and Rowbot Systems (Cavender-Bares & Lofgren, 2016). Each utilizes a combination of GNSS, LIDAR, IMU, and cameras for localization and perception as they traverse row crops (corn, sorghum). A well-adopted approach taken to perform the navigation autonomously is to 1.) Fuse real-time kinematic (RTK) GNSS with IMU data to obtain an estimated robot pose, 2.) Perform waypoint pursuit and path following, 3.) Sense the environment using the onboard vision sensors (cameras and LIDAR), 4.) Use a data-intensive architecture (e.g., video) to estimate plant stalk locations relative to the robot's frame via a heuristic, and 5.) Construct a map of the environment to redirect the robot along a more suitable path. The navigation approach very closely mirrors the standard method of path planning and obstacle avoidance for robots in industrial settings despite the agricultural environment being patently different. Others have considered machine learned approaches (Xue et al., 2012; Cuaran et al., 2023; Sivakumar et al., 2021).

To our knowledge, the longest demonstrated autonomous traverses for in-row UGVs in broadleaf crops is currently: 386.9 m in manicured, gap-free fields; 56.1 m in production fields; 47.5 m in fields with gaps without machine learning (Velasquez et al., 2022); and 485 m in a manicured field with machine learning (Sivakumar et al., 2021), highlighting the challenge of robust locomotion within mature row-cropping environments. Here, navigation is made challenging by narrow row-crop alleys, tight row curvature making turning difficult, GNSS degradation due to multi-path effects and canopy cover, and planting variation and gaps within rows. Visual sensing, in particular, is burdened by aliasing, lighting variation, occlusion from weeds and leaves, and

cropping environments appearing unstructured due to deformable structures like leaves and weeds.

3.2. Tactile sensing in agriculture

To overcome the unique challenges with visual navigation in dense vegetation, some have considered utilizing *tactile* means of sensing the environment through feelers, bumpers, whiskers, and haptic and piezoelectric devices (Prescott et al., 2009; Andresen et al., 2022; Girão et al., 2013), often paired with a visual sensor like a camera or LIDAR. Commercially, companies like Reichhardt offer tactile feeler sensors to be placed on the corn snout of a combine header. Paired with ultrasound, their system operates as a row finder for steering guidance while harvesting (Delavarpour et al., 2019). Visual systems in rice paddy fields face many of the same problems as in corn. To enable targeted interplant spraying from a UGV, Chen et al. (2024) developed a paired tactile-light sensing system to localize nearby rice-stem bases, comprising a diffuse reflection sensor to determine when the vehicle is below occluding features (i.e., when nearby a plant), a piezoelectric film sensor to detect contact pressure, and a flex resistive bending sensor for rice plant positioning. They found the system could accurately detect more 80 % of nearby rice plants using various machine learned approaches to characterize the data. Gy and Bajpai (2023) developed a visual-tactile approach to extract features of a cornfield using cameras and haptic sensors. They characterized the system's ability to identify "hard" contacts (with a stalk) from "soft" contacts (with leaves and weeds) and generate an appropriate control signal to redirect a robot, finding that the system "increased traversability" in that it filtered out 70 % of soft features that visual systems would believe were non-traversable. While tactile sensors have been used to detect stalks previously, few researchers, if any, have explored using *only* tactile sensors to navigate autonomously below a crop canopy. Reflecting this, our objective is to investigate the ability to detect and localize corn stalks using information originating solely from tactile inputs and then assess navigation performance using only this information. In this sense, our tactile system is inspired by the navigation of an imagined blind individual. On contact with an obstacle, receptors in the hands convert skin deformation into signals to send to the brain. There, sensory inputs merge to create a spatial representation of the environment independent of the input modalities and preliminary path forward is determined (Loomis et al., 2012; Chebat et al., 2018; Giudice et al., 2011). In the case of the blind person, the spatial information available to them is constrained by the individual's arm span, so the planned path is shorter, directed forward, and redetermined more regularly. Similarly, protruding feelers can provide a robot with pre-emptive awareness of a nearby obstacle by establishing contact with these features prior to the actual robotic platform. Performance criteria include the detection accuracy of nearby stalks, the error associated with an individual corn stalk position, and the maximum distance traversed autonomously prior to needing an intervention to compare to performance of the visual-fusion benchmarks of Velasquez et al. (2022) and Sivakumar et al. (2021).

3.3. Problem Definition

The stated problem is to, in real-time, proprioceptively identify and position nearby stalks, populate an estimated map of the environment, and then plan and execute a path toward a goal, within a semi-structured, dynamic environment. We assume the vehicle has no initial knowledge of the environment, i.e., $\hat{\mathcal{P}}_{obs}|_{(s=0)} = \emptyset$; that the vehicle begins with a sequential list of goal points placed at the ends of row alleys, approximately centered between the rows; that the start-up pose of the robot is not kinematically constrained (e.g., not directly facing a row); and that viable paths exist between the goals. I.e., let, $\mathbf{w}_i \in \mathbb{R}^2$, $\mathbf{W} = \{\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_n\}$ be a sequence of goal points, in a weighted directed graph, $\mathcal{D} = (\mathbf{V}, \mathbf{E}, \mathbf{S})$. For each $(\mathbf{w}_i, \mathbf{w}_{i+1})$, where $i \in [1, n-1]$, a sequence of edges $(e_1, e_2, \dots, e_{m-1}) \in \mathbf{E}$, and a sequence of vertices $(v_1, v_2, \dots, v_m) \in \mathbf{V}$ exist s.t. an open, directed path, can be found between them, $\mathcal{S}(e_j) = (v_j, v_{j+1})$ for $j = 1, 2, \dots, m-1$, where e_1 begins at $\mathbf{w}_i$ and e_{m-1} terminates at $\mathbf{w}_{i+1}$ to connect adjacent goals. We propose an optimal control problem to find a path, by minimizing a cost function $J(\mathbf{x}_r(s), \mathbf{u}_r(s), s_{max})$ for the vehicle pose, $\mathbf{x}_r(s) = [x(s), y(s), \beta(s)]^T$, control inputs, $\mathbf{u}_r(s) = [v_{left}, v_{right}]$, and the length of the entire path, $s_{max} = \sum_{i=1}^{n-1} \|s_i\|$, where v , v_{right} , and v_{left} are the vehicle's center, right and left linear speeds, respectively; x and y are the location of the vehicle center in a global frame relative to its start position; and β is the heading angle. The cost function is determined iteratively, in real-time, based on the positions of detected plants. The constraint $\frac{d\mathbf{x}_r(s)}{ds} = f_{kin}(\mathbf{x}_r(s), \mathbf{u}_r(s))$ ensures kinematic feasibility, where each element of vectors $\mathbf{x}_r(s)$ and $\mathbf{u}_r(s)$ is bounded. Initial and terminating vector states are given as $\mathbf{x}_r(0) = \mathbf{x}_0$ and $\mathbf{x}_r(s_{max}) = \mathbf{x}_r(\mathbf{w}_n)$. Similar conditions are given for $\mathbf{u}_r(s)$. f_{kin} is the kinematic model of the vehicle's steering, 4-wheel differential drive, with the vehicle pose given by $\frac{dx(s)}{ds} = v \cos(\beta(s))$, $\frac{dy(s)}{ds} = v \sin(\beta(s))$, and $\frac{d\beta(s)}{ds} = \frac{v_{right} - v_{left}}{L}$, where L is the wheelbase. $\mathbf{u}_r(s)$ represents the commanded left and right-side speeds. The collision-avoidance constraint is $\mathcal{B}(\mathbf{x}_r(s)) \cap \mathcal{P}_{obs} = \emptyset$, where $\mathcal{B}$ is the region occupied by the vehicle footprint and $\mathcal{P}_{obs}$ is the area occupied by obstacles (plants). Finally, the path-to-be-found is directed, so we assume the vehicle does not drive backward and bound the inputs s.t. $v_{right}, v_{left} \geq 0$ and $|v_{right} - v_{left}| \geq \alpha$, where α limits the vehicle angular rate. Our proposed tactile solution to this navigation problem is presented in the subsequent sections, first discussing local obstacle detection and positioning using our sensor, and then, navigating using the output spatial information.

4. Tactile sensing system

Obstacle detection and mapping is performed by the sensor system shown in Fig. 5, comprising three main parts: a mechanical device inspired by the human hand (providing sensing), a classifier to detect contact forces (providing perception), and kinematic algorithms to localize and map obstacles based on the contact states (providing spatial awareness). The navigation approach described in subsequent sections is then independent of the sensory input modalities but reflects the reduced knowledge of the environment.

4.1. Stalk sensing

The feeler comprises a paddle pinned on one end, a set of springs that passively recenter the paddle about the pin, and a rotary encoder that provides the robot with proprioceptive data of the joint state. In simulation and on the real-world prototype vehicle, measurement occurs at 125 Hz. The mechanism acts as a simple force sensor such that when mounted to the front of a moving vehicle, its angle will change upon contact with the environment. While the cropping environment may appear unstructured to visual sensing systems (and is described this way in the literature), it is instead highly structured with a messy, deformable overlay of leaves. With just two of these sensors mounted to the leading edge of a vehicle, the joint state of each sensor, $\theta_k = [\theta \ \dot{\theta} \ \ddot{\theta}]^T$, can be used to determine this organized structure in the immediate periphery of the robot frame, while it is in motion. Measuring joint angles in this way has been shown as an effective sensing modality to proprioceptively extract information about various system states for a moving UGV (Gronewold et al., 2021).

4.2. Contact perception

The contact state of the sensor provides *perception* which contextualizes a given contact into a stalk to-be-mapped. Contact behaviors are modeled as a finite state machine (FSM), $S_k = T(S_{k-1}(\theta), C(\theta))$, where the joint state of the sensor is the input to the state transition function, T , for the conditions of transition, C . Despite the sensor being passive, the state machine enables real-time classification at each timestep to delineate between joint states characteristic of contact-driven forces vs. system vibration. Paddle springs, in addition to providing well-tuned transition thresholds, filter out flexible obstacles like weeds, leaving only rigid structures to be localized. In its simplest form, the classification determines whether the sensor is in contact or not (2 cases). The deployed classifier is shown in Algorithm 1 and Fig. 5, which includes

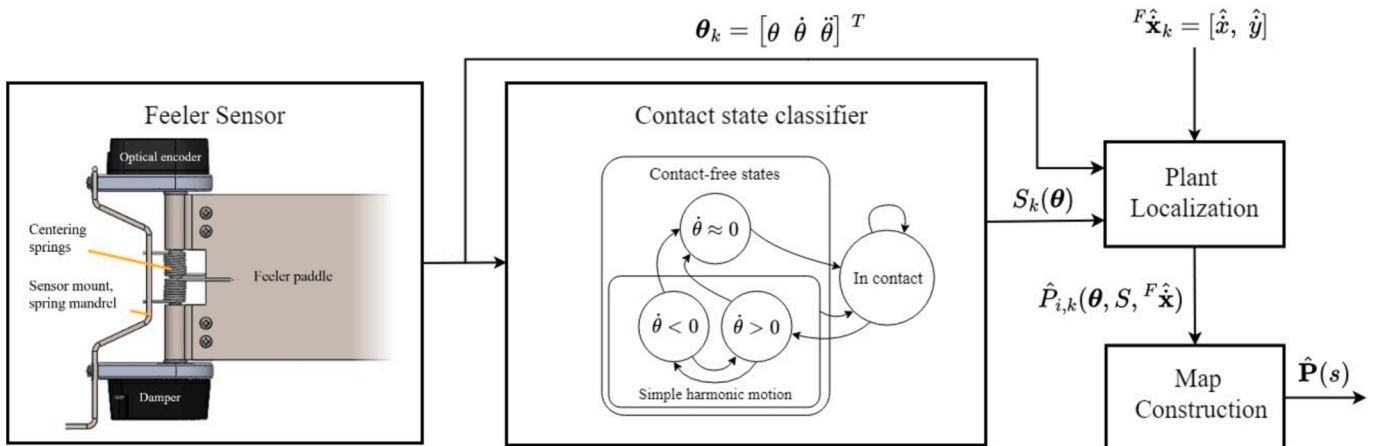


Fig. 5. Tactile Sensor Embodiment. The device to acts as a simple force sensor. The joint state is supplied to both a contact-state classifier that identifies if the sensor is in contact and a plant localization block which uses an estimate of the speed at the sensor to estimate stalk positions at each timestep. These localizations are transformed into a global frame and utilized to append and modify the supposed map of the environment.

additional diagnostic cases each of which is still one of the original two cases. The additional diagnostic cases include simple-harmonic motion with an increasing or decreasing angle, steady-state (even if the sensor sticks at a non-zero angle), or high-risk contact states where the sensor is heavily deflected. According to Algorithm 1, an identification of the joint state is exemplified as follows: if the sensor was previously in contact, $S_{k-1} = \text{"contact"}$ (or some equivalent numerical encoding), conditions $[C_9, C_{10}, C_{11}]$ will be checked sequentially to determine if the sensor has transitioned to **a.)** a crashworthy state (veering toward the row), C_9 : if $\theta(i) > 75^\circ$; **b.)** simple harmonic motion returning the sensor to home, C_{10} : if $\forall i \in [k-h, k], \dot{\theta}(i) > 25^\circ/\text{s}$, for a backward history of h many timesteps; or **c.)** to a steady-state sensor angle, C_{11} : if $\forall i \in [k-h, k], |\dot{\theta}(i)| < 25^\circ/\text{s}$ and if $\forall i \in [k-5, k], |\ddot{\theta}(i)| < 1000^\circ/\text{s}^2$. If no conditions return true, the contact state remains the same. The conditions of the transition function are heuristics of the joint states tuned to reflect performance for a given model (simulation, real-world sensor, varying sensor lengths, system vibration, robot size, etc.). The sequence of conditions for a given case additionally affects the dynamics of the contact state.

$S_0 = \text{"Steady State"}$
loop:
 $\theta_k \leftarrow \text{CallFeeler}()$ // Measurement
 $S_k = T(S_{k-1}(\theta), C(\theta))$ // Contact state transition
if $S_k = \text{"Contact"}$:
 ${}^F\hat{P}_{i,k} \leftarrow \text{PerformLocalization}(S, \theta, {}^F\hat{x}_k)$
 ${}^G\hat{P}(s) \leftarrow \text{PerformMapping}(\hat{P}(s), \hat{P}_{i,k})$
function $T(S_{k-1}(\theta), C(\theta))$:
// Case(S_{k-1}) Contact state to return **If** $C(\theta)$,
 $S_k = \begin{cases} \text{"Steady State"}, & T = \begin{cases} \text{"Contact"}, & C_1 \\ \text{"S. H. M. +"}, & C_2 \end{cases} \\ \text{"S. H. M. +"}, & T = \begin{cases} \text{"Steady State"}, & C_3 \\ \text{"Contact"}, & C_4 \\ \text{"S. H. M. -"}, & C_5 \end{cases} \\ \text{"S. H. M. -"}, & T = \begin{cases} \text{"Steady State"}, & C_6 \\ \text{"Contact"}, & C_7 \\ \text{"S. H. M. +"}, & C_8 \end{cases} \\ \text{"Contact"}, & T = \begin{cases} \text{"Near Crash"}, & C_9 \\ \text{"S. H. M. +"}, & C_{10} \\ \text{"Steady State"}, & C_{11} \end{cases} \\ \text{"Near Crash"}, & T = \begin{cases} \text{"S. H. M. +"}, & C_{12} \\ \text{"Steady State"}, & C_{13} \end{cases} \end{cases}$
return S_k

Algorithm 1. Joint State Classification

4.3. Spatial awareness

The contact state is synchronously sent alongside the joint state to a localization block that converts the perceived sensory information into spatial information. At each timestep in contact, the block outputs an estimated stalk location in the reference frame of the sensor, ${}^F\hat{P}_{i,k} \in \mathbb{R}^2$. This is done through simple trigonometric relations illustrated in Fig. 6. In the sensor frame, F , the plant location at each timestep is related to its contact length along the paddle sensor, l , and the sensor angle by $d^2 + p^2 = l^2$, $d \cos(\theta) = l$, and $p \sin(\theta) = l$, where p is the sensor deflection distance along the robot's length and d is the perpendicular distance of the stalk location. Assuming the incident line of the plant contact is parallel with the direction of motion of the vehicle (i.e., zero-slip angle), then $d_k \cong d_{k+1}$. With an estimated forward velocity and yaw rate of the robot transformed into F to estimate the velocity at the sensor origin, $\hat{v} = {}^F\hat{x}_k$, the change in p is then $p_{k+1} - p_k = \hat{v} \Delta t$. From this, $d_{k+1} \tan(\theta_{k+1}) - d_k \tan(\theta_k) = \hat{v} \Delta t$. Substituting for d_{k+1} , then the estimated stalk location in the sensor frame is ${}^F\hat{P}_{i,k} = (d_k, p_k)$, where:

$$d_k = \frac{\hat{v}(t_{k+1} - t_k) \cos(\theta_{k+1}) \cos(\theta_k)}{\sin(\theta_{k+1} - \theta_k)} \quad (1)$$

$$p_k = d_k \tan(\theta_k) \quad (2)$$

Finally, non-sensical stalk location estimates (e.g., outside the sensor range) are filtered heuristically.

The estimates are output to a mapping block where they are transformed into the global frame, G , by ${}^G P = {}^G T_M {}^M T_F {}^F P$, where ${}^M T_F$ is the transformation (dependent on the sensor home angle and pin location) of a stalk location in frame F to the robot frame M and where ${}^G T_M$ is the transformation matrix from M to G (as a function of the robot position and heading). The global obstacle location is low-pass filtered to smooth contact state vibrations caused by short contact detections (e.g., due to paddle bouncing or aggressive wheel-motor start-up torque). Then, the filtered, transformed stalk location is used to update the map of the environment. The time between the start and end of a contact period and an average spatial estimate across this period are determined. If any other mapped stalk is within a threshold of the stalk-to-be-added (e.g., 2 cm), we average the two locations and replace the existing stalk with the average. Otherwise, the new stalk location is added to the map. This means the estimate improves as the vehicle advances and a detected stalk slides along the paddle surface. It is also valuable to identify each localized stalk's row affiliation by storing information to indicate the sensor that performed each detection. If subsequent stalk additions share

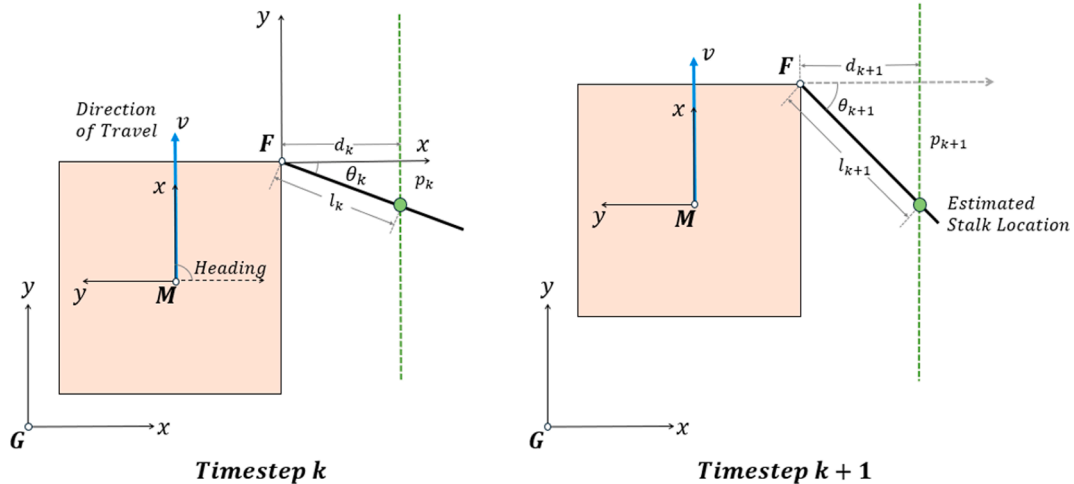


Fig. 6. Kinematics of Zero-slip Stalk Localization. At each timestep, the estimated stalk location in sensor frame F is determined through trigonometric relations followed by filtering. Localizations are then transformed to robot frame M and global frame G and incorporated into a global list of mapped plants.

a parent sensor and they are closer than the typical largest gap in a row (e.g., 120 cm), we can determine if a given plant shares a row with another plant. This embedded sensor system (the passive feeler, the heuristic contact classifier, and the position algorithm), allow a robot to map a cropping environment as it advances, without any knowledge a priori.

5. Blind navigation

The mapping system described in Section 4 functions as an independent sensor system that can be used with or without incorporating it into autonomous navigation (e.g., during teleoperation). To navigate autonomously, we use the constructed map alongside a common planning strategy as shown in Fig. 7. The system uses a well-known graph traversal algorithm, A^* , to find an optimal path for the vehicle to follow given the provided spatial information, and pure pursuit, a traditional path following algorithm. The output of A^* is a reference path, s_{ref} , calculated along a grid with no diagonal edges and is therefore not kinematically feasible for the robot. Pure pursuit is used to smooth this path by repeatedly calculating a turning center and reference robot yaw rate to reach a lookahead point that is a fixed distance ahead of the vehicle along the reference path. The approach is well documented in robotics literature, but two modifications are made with inspiration from how a blind human may approach the problem.

list, select the node with the lowest cost, i.e., $n^* = \underset{n \in \text{OpenSet}}{\operatorname{argmin}} f(n)$ where $f(n) = g(n) + h(n)$, for node n , the actual cost (often called cost-to-come or path-cost), $g(n)$, and the planning heuristic, $h(n)$. 4.) Move the selected node to the closed list, evaluate its neighbors in the graph, and add them to the open list; because of this A^* is said to have a planning frontier of open nodes. 5.) Repeat the process until the frontier dies (no solution) or until the goal point is in the closed list, at which point the full path is reconstructed by advancing back from the goal through all parent nodes to the start goal. In $\mathbb{R}^2$, the path cost of a given node is typically given by the Manhattan distance through all parents of said node for r parents.

$$g(n) = \sum_{i=1}^r |x_n - x_{n-j}| + |y_n - y_{n-j}| \quad (3)$$

The heuristic function is usually a Euclidean distance estimate of the path to the same node, because it is admissible (i.e., the heuristic underestimates the true cost $h(n) \leq h^*(n)$ for all nodes). The map of the environment is also usually modelled as a bitmap or occupancy grid where occupied regions are considered outside of the bounds of the exploration space. To maintain admissibility and optimality of the path, we instead minimize $f(n) = g'(n) + h(n)$ where $g'(n) = g(n) + o(n)$ and $o(n)$ is a penalty associated with the obstacles and undesirable vehicle paths defined as

$$\begin{aligned} o(n) &= o_{stalks}(n) + o_{rows}(n) + o_{kinematics}(n) \\ &= \sum_{i=1}^{|\mathcal{P} \subseteq \hat{\mathbf{P}}(s)|} C \cdot e^{-\gamma \|n - \mathbf{p}_i\|} + \sum_{j \in \mathcal{A}} \sum_{k=1}^{N_j} \left\{ \sum_{m=1}^N C \cdot 1 \left(\left\| \mathcal{L}_j^{(k,m)} - n \right\| < g \right) \right\} + C \cdot 1(|\Delta \beta_{s_0, n}| > \theta_r) \cdot 1(\|s_0 - n\|) \end{aligned} \quad (4)$$

5.1. Blind adapted A^* with obstacles

The general approach to A^* is to minimize an evaluation (i.e., cost) function, $f(n)$, as follows: 1.) Define the search bounds and the start and goal points for which a path will be determined 2.) Beginning at the first point (node), initialize an open and a closed list of the nodes to be explored and the nodes already explored, respectively 3.) From the open

The three terms in $o(n)$ are interpreted as a penalty associated with a node's proximity to a mapped plant in the exploration space, the cost associated with a line between two plants within a given row to penalize interrow traversals, and a penalty constraining the beginning of the planned path to be oriented approximately in the same direction as the current robot heading so that the planner does not yield a kinematically infeasible path. C , γ , g , θ_r , and N are parameters defining the penalties,

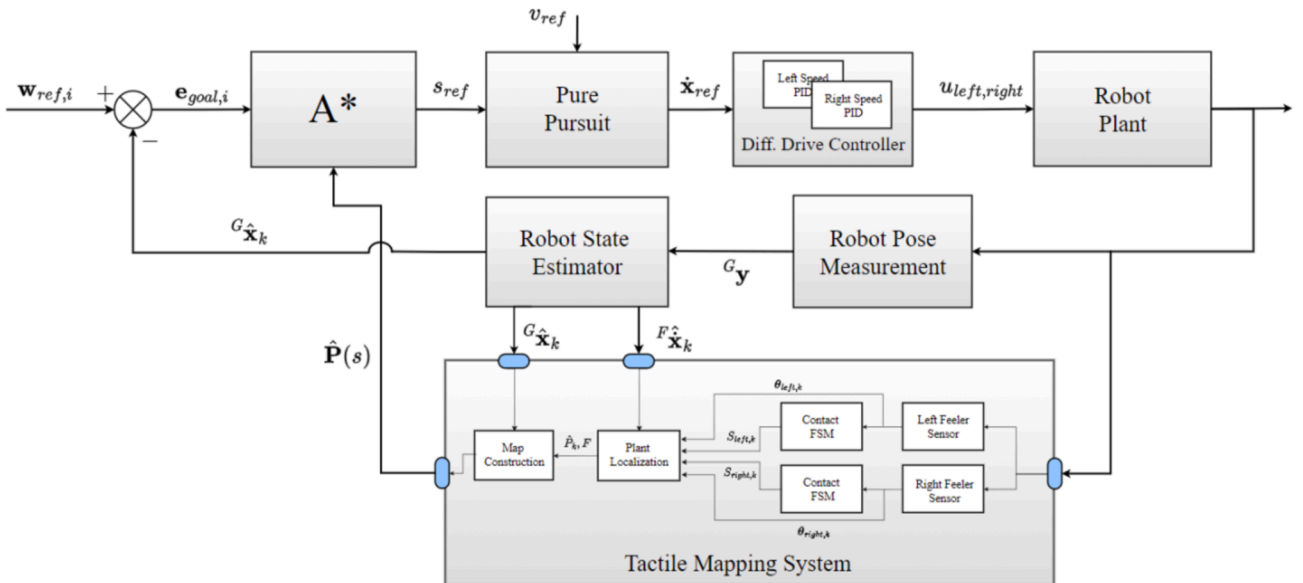


Fig. 7. Block Diagram Model of Blind Navigation. The navigation system closely mirrors visual navigation systems, making use of A^* and pure pursuit to navigate autonomously by touch.

the exponential buffer of the penalty around a given plant, the grid size of the planning, the heading angle range threshold for which there will be no additional penalty, and the number of points evaluated between successive plants within a row, respectively. In eq. (4), $\mathcal{P}$ is the subset of plants in the original map inside the A* exploration space, p_i is an individual stalk obstacle in the exploration space, $\mathcal{R}$ is the set of unique rows in the exploration space, N_j is the number of line segments in a row (one between each successive pair of stalk neighbors), $\mathcal{L}_j^{(k,m)}$ is the m -th point on the k -th line segment in row j , $1(\cdot)$ is the indicator function, and $\Delta\beta_{s_0,n}$ is the change in robot heading angle between the start of the path s_0 and the node being evaluated. Across simulation and real-world testing, we found the following parameters produced quality path plans conducive to navigating the testing environments: $C = 50$, $\gamma = 20$, $g = 5$ cm, $\theta_r = 30^\circ$, and $N = 10$.

An example of the planner is shown in Fig. 8, which is a screenshot from video 1, demonstrating these blind adaptations to route construction by using the spatial map in the evaluation function of A*. Because the tactile navigation system can only map plants within the immediate periphery of the vehicle, the point that A* generates a path toward is not a global goal point $w_i \in \mathbf{W}$. Instead, the A* goal point is a fixed-short distance in front of the vehicle (e.g., 3 m) s.t. the end of the path plan is greedy and points toward the next goal in $\mathbf{W}$. This means the path is directed toward the global goal points, despite only planning a short distance ahead. The small search space (~ 3600 nodes) enables the path planner to be used in real time (160 Hz + from our testing of the simulated path planner).

5.2. Pure pursuit of a point right in front of You

The path planner produces a jagged path that is kinematically infeasible for non-holonomic vehicles. Pure pursuit is used to smooth the motion of the robot along the planned path by identifying a point to follow that is a fixed distance ahead of the robot on the path, called the lookahead distance (L_d), at each timestep. Trigonometry can then be used to determine the wheel-motor speed commands needed for a differential drive robot to pursue the given point via a circular arc. The following principles are illustrated in Fig. 9. Pure pursuit is a cross-track

error proportional controller that considers the distance over which the cross-track error must be minimized. For a cross-track error ρ taken as the perpendicular distance between $\mathbf{x}_r$ and the lookahead point, the path control input of the vehicle (i.e., the curvature of the circular arc) κ , has the following geometric relationship, $\kappa = \frac{K_p \rho}{L_d^2}$, where K_p is a proportional gain that adjusts responsiveness. Often $K_p = 1$ is used, and L_d becomes the only tuning parameter. For fixed ρ , smaller L_d produces more aggressive control inputs. Many engineers tune L_d as a function of the vehicle's nominal forward velocity, but for the prescribed application speed is not a limiting factor. Instead, the lookahead distance is tuned as a function of its spatial relationship to the sensors so that the lookahead distance is always ahead of the vehicle body, but behind the forwardmost sensor. In practice, A* becomes greedy beyond the range of the sensor, so the lookahead point must be within the footprint of the vehicle, behind the forwardmost sensors to respond to the spatial information available to the blind system in time to correct course. This is not unlike how a blind individual navigates, first feeling what is directly ahead, then planning slightly further, and finally, advancing to a point within reach before repeating. The tests and findings of using this tactile architecture in simulation and on a robot in a production cornfield are presented in Sections 6 and 7, respectively.

6. Mapping tests in simulation

6.1. Physical model construction

The tactile mapping system is first implemented and tested in a Matlab simulation environment. The simulation includes both a physical model of the robot and sensory systems, and the proprioceptive model of the environment described in Section 4. The physical sensor model parameters are established based on measurements of real-world spring dynamics and paddle dimensions. The contact-free paddle system is governed by $I\ddot{\theta} + b\dot{\theta} + k\theta = 0$ with $k \cong 0.67$ Nm/rad, $b \cong 0.0003$ (Nm·s)/rad, and $I \cong 1.21 \times 10^{-5}$ kg·m². During contact, the system is driven kinematically by the position of the plant in contact. The model assumes the sensor is moving at a known rate. True contacts are set by determining the closest plant within some active range of the sensor. If this

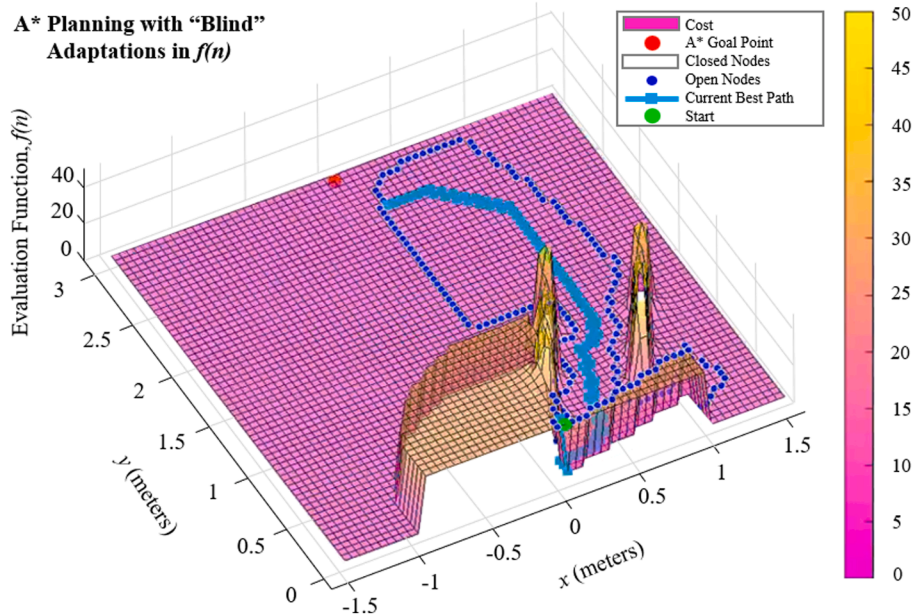


Fig. 8. A* Planning with Blind Adaptations. Our planning incorporates routed based navigation with respect to the rows adapted to the limited spatial information available to a blind system.

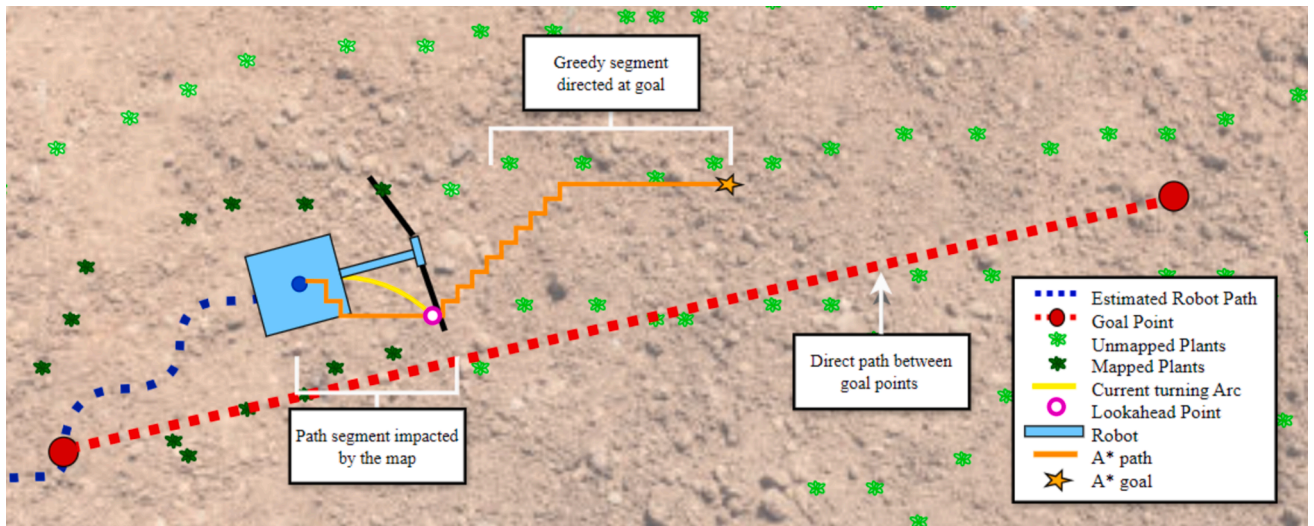


Fig. 9. Lookahead Point and Planned Path. A blind human will likely navigate poorly by assuming their path is clear substantially ahead of what they can directly feel. The planning of a blind mobile robot incorporates the same thinking.

minimum distance is less than a paddle length from the sensor pin, we begin to calculate the minimum distance between the plant and an interpolated list of paddle positions along the paddle length. Below a threshold (0.5 cm), the true contact state is set to “on,” and its position is manually set via its angle, such that paddle remains in contact with the point until it has been passed. The system dynamics transition back to the equation of motion for rotational simple harmonic motion after contact has finished. Finally, we assume the sensor does not always return to mathematical equilibrium due to Coulomb friction in the pin bearings. This is modeled with temporally random sticking behavior within $0 \pm 15^\circ$ which sets the sensor angular velocity to 0 when following simple harmonic motion. This is included such that the finite-state machine of Section 4.2. is tested against real-world sensor dynamics. Model construction and the behavior of the real vs simulated sensor dynamics for similar inputs are shown in Fig. 10.

6.2. Detection assessment

The contact detection system is evaluated by simulating robot movement along a row of unevenly-spaced stalks as in Fig. 10, where sensor measurements include white noise on the angle ($\mu = 0.0^\circ$, $\sigma = 0.02^\circ$). The joint state classification is visualized as in Fig. 11a by plotting the perceived contact state in step with the joint state angle. Performance of the finite state machine is determined both by considering the number of detected contacts against total viable contacts over an extended period of the simulation, and by considering the confusion matrix of the classifier. For a nominal speed of $v = 0.2$ m/s over ~ 30 min of simulated driving comprising 220,000 + instances of input joint state features, we found the classifier identified 84,271 true positives, 4,405 false positives, 1,872 false negatives, and 131,016 true negatives for an accuracy of $(TP + TN)/(P + N) = 97.2\%$. Temporally, the classifier closely follows the actual contact behaviors of the system as in Fig. 11b, slightly overshooting or undershooting the real contact count value over time.

6.3. Positioning assessment

The sensor system is tested in a simulated cornfield to assess mapping performance while following a predetermined, traversable path (“open-loop”), illustrated in Fig. 12a. A set of sensors is deployed on a simulated differential drive robot that follows a simple straight path between goal points. While driving, the robot populates a map, but its control reflects the predetermined path. Corn rows are constructed on either side of the path such that the inter-row spacing is 76.2 cm on average and the intra-row spacing is 22.3 cm on average. The position of the stalks has zero-mean Gaussian randomness with $\sigma = 2.8$ cm about the expected stalk locations, as determined by estimates from real-world measurements of cornfield characteristics. The vehicle position is sampled at 4 Hz, comparable to the sample rate of NMEA strings arriving from a GNSS system. Consequently, the global position of the sensor (and therefore the mapped stalk locations) reflects an extrapolation of the vehicle’s last known position and velocity. Under the conditions described, the system successfully detects all plants within the range of the sensor array. The mapping system also demonstrates the improvement of the localization as the stalk slides along the sensor paddle length, leading to an estimated spatial accuracy of 1.9 cm with respect to the true stalk location in simulation.

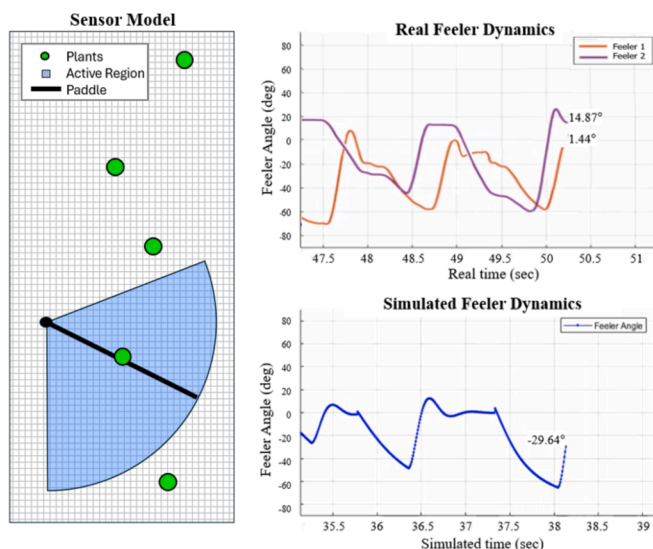


Fig. 10. Physical Sensor Abstraction. Stalks are assumed to approach the simulated sensor at a set rate from a variety of incident angles and distances from the sensor pin. The system was tuned until the simulated joint state approximates the joint state of real-world sensors for similar inputs.

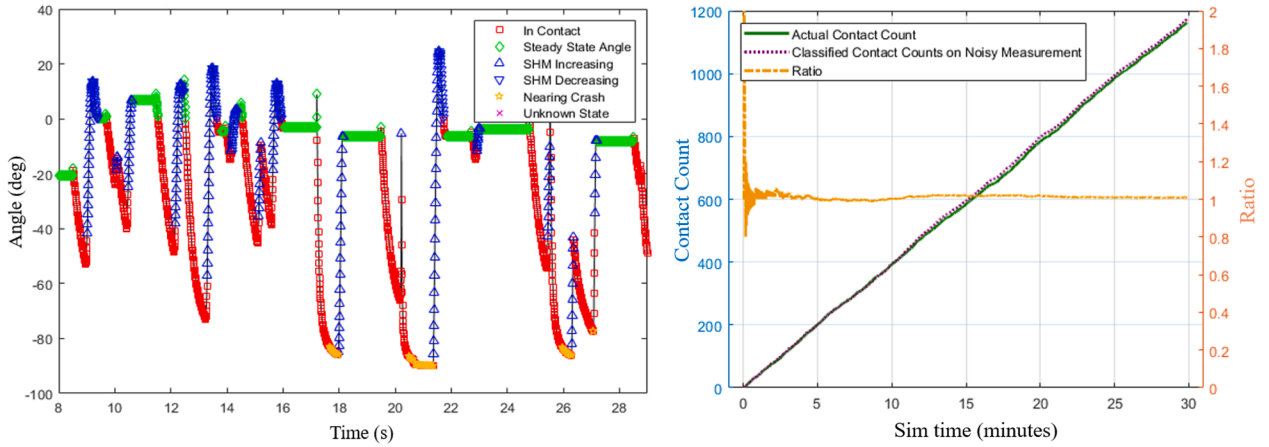


Fig. 11. Contact State Classification and Performance Over Time. (a): The finite state machine is modelled alongside the physical and measurement model of the sensor to test real-time performance of the contact detection system. (b): The performance of the simulated classification system over an extended period demonstrates the ability to accurately identify if contact has occurred.

6.4. Simulated blind navigation

The full navigation system of Section 5 is deployed in the same simulation environment to test the capability of blind, autonomous navigation using the tactile system for closed-loop spatial awareness. The vehicle is given the same goal points as the open-loop system, but the rows are modified such that the center of the row alley is no longer aligned with the straight path between the goals. Row gaps are introduced by removing 10 % of the plants in the simulated cornfield at random. Row curvature is introduced by making the row centers follow a sinusoidal function along their length. Fig. 12b shows the ability of the robot to navigate the environment – none-of-which is known *a priori* – despite being blind, as indicated by its path in the global frame. Video 1 further highlights the performance of the system. The Video demonstrates how the map is constructed over time for the robot and how the vehicle navigates based on the limited spatial information available to it. Notably, the vehicle tends toward greedy behavior in its path planning as the end of the A* reference path is always directed at a goal point. The vehicle initially assumes the straight path between the two points is optimal because it has no information of the environment, shown in Fig. 12 as the dashed red lines; in our simulation, the navigation remains highly robust up to 3.2 m in cross-track error between the real row center and the straight-line path between goals the vehicle assumes at start-up. With four sensors, we found the simulated vehicle could travel an approximate average distance of 38 m prior to encountering an unrecoverable state ($n > 30$) within the curved path, while the average distance prior to becoming unrecoverable on a straight path is 70 m ($n > 20$). A second vehicle was tested under the same conditions using only two feeler sensors as in Fig. 12b. Video 1 includes an animation of this vehicle traversing the entirety of the 100 m curved course, with an approximate maximum curvature of $\kappa = 0.15$ over a 10 m span. In practice, we found the simulated vehicle with two feelers could reliably travel an average distance of 35 m down the curved setup ($n > 30$) and approximately 65 m in a straight row alley ($n > 20$).

7. Real-world testing

7.1. Robot design

The tactile sensing and mapping modality is further tested through a real-world embodiment of the vehicle, which is summarized in Fig. 13. The robot is a modified Pioneer 3-AT operated via a custom ROS2 (Robot Operating System) package. An NVIDIA Jetson manages the system architecture in Fig. 7 by embodying each system block as a Python node and passing messages between them using ROS topics. The estimated

map of the environment is passed from the mapping node to the path planning node at each timestep using a ROS service, demonstrating the reductions in data and computation compared with vision. At navigation start up, all nodes are launched concurrently. The wheels are driven by belt coupled DC motors and controlled using DC motor drivers. A microcontroller running embedded PID speed control receives left and right reference speed updates via serial from a ROS subscriber callback function. The robot is optionally teleoperated via a ROS node and a gaming controller communicating with the base through a Bluetooth module on the Jetson board. From the controller, users can drive the robot by throttle or joystick control; start, stop, and modify all sensor nodes; initiate a data-storage node; and more. An integrated GNSS unit (an RTK Facet, RF shielded L1C/A, L2C TOP106 antenna, and ZED-F9P u-blox module) is affixed to the robot on a short mast. Industry-standard NMEA messages are piped serially at ~ 4 Hz to a ROS node where they are published to various topics to monitor the positioning state from the command line. During navigation, longitude, latitude, and course-over-ground measurements from the GNSS receiver are converted into the robot state measurement, $\hat{\mathbf{x}} = [x, y, \theta]^T$, in an east-north-up (ENU), meter-based frame, relative to the startup pose of the robot using a Haversine distance. The mobile GNSS unit receives RTK corrections by an additional GNSS receiver operating as a base station on the periphery of the cornfield and communicating RTCM-104 messages regularly to the roving GNSS receiver via two full-duplex 500mW, 915 MHz telemetry radios with 6' whip, tilt antennas (monopole). The real-world feeler sensor is also shown in Fig. 13. Measurements are performed through an encoder transduction process which provides sensory information of the internal joint angle as the feeler is deflected by obstacles.

To visualize the vehicle's understanding of itself and the environment, the robot makes use of optional headless functionality using a detachable monitor connected via HDMI. The current believed state (both of the vehicle and the environment) is revealed from ROS2 using a custom node to manage an Rviz (ROS Visualization) process, where we display a Unified Robot Description Format (URDF) model of the robot oriented according to its estimated system states managed by "tf", a native ROS system. The tf system keeps track of multiple coordinate frames to maintain their respective relationships and performs the necessary frame transformations in the feeler mapping. Finally, we deploy a custom broadcast service that publishes a plant stalk location to be added to the real-time display in Rviz. The exposed model is shown in Fig. 14. The real-world robot is tested, refined, and validated in an analogue testing environment of bamboo poles, and then deployed in a cornfield.

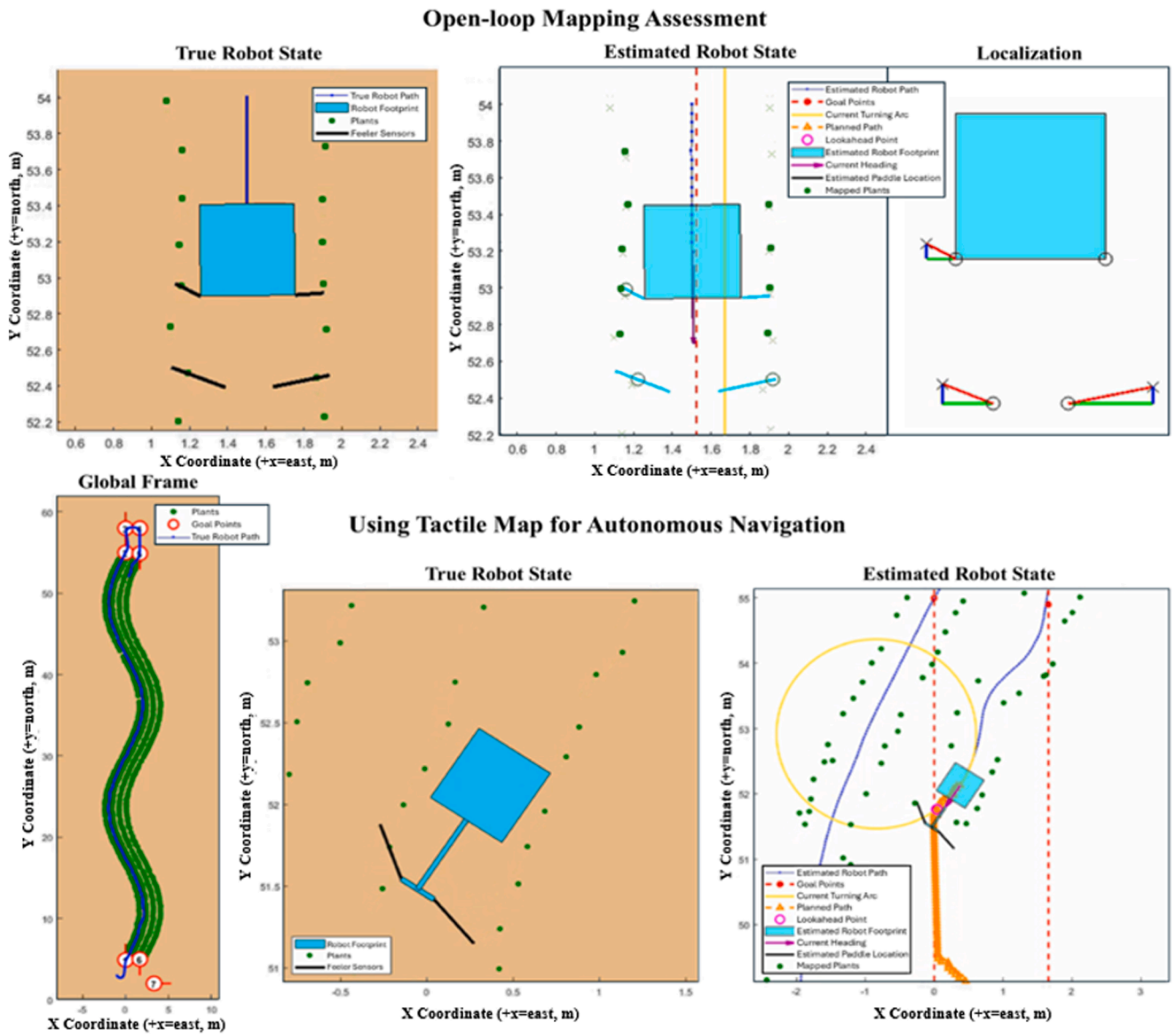


Fig. 12. (a; top): *Open-Loop Mapping Simulation Environment*. The mapping system is tested for performance on a simulated differential drive robot, which follows a predetermined path directly down the center of a row. During its traverse, the stalk centers are localized and transformed to the robot frame to be visualized alongside the estimated robot state. (b; bottom): *Closed-Loop Mapping for Blind Navigation*. The simulation environment demonstrates an autonomous navigation system that is moderately robust against high row curvature, row gaps, and substantial plant position variance.

7.2. Analogue test environment

The environment shown in Fig. 15 was used to assess the tactile navigation system and to validate the ability of the robot to localize plant stalk locations. The general structure of the course is defined through a combination of hand measuring and RTK-GNSS assisted surveying such that the actual row alley (shown in orange) deviates two meters from the vehicle's initial assumption of an obstacle-free path (red). As in the simulated tests, the vehicle begins with predefined goal points at the ends of the row alley, approximately 40 m apart here. Bamboo stakes are placed along the two rows, organized with an average inter-row width of 76.2 cm, an intra-row width of 28.0 cm, and an approximate variance of $\sigma^2 = 9$ cm about the stake positions under perfect planting to imitate the pseudorandom nature of a mature cornfield. Finally, the real-world positions of bamboo stakes were manually surveyed ($\sigma < 1.4$ cm) using an RTK-corrected mobile receiver such that estimated stake locations could be validated against their known

locations within the limits of uncertainty in the points we validate the mapping system against. Two types of tests are performed in this environment. First, the mapping system is initiated, and the vehicle is teleoperated along the path, keeping the vehicle as centered along the row alley as best as possible. Mapped stakes were recorded for later comparison to the real-world locations. In the second set of tests, the full navigation system is activated, and the vehicle is navigated autonomously down the row. While the stake positions are known during validation testing, the course changed incrementally during autonomous navigation tests and therefore the stake positions in each of these tests are not known perfectly.

7.2.1. Detection and positioning validation

To first validate the mapping system, the stake positions as estimated from the teleoperated vehicle are compared with RTK-GNSS validated, real-world stake locations in the planned course in Fig. 16. Several types of classification error are identified. In general, the teleoperator focused

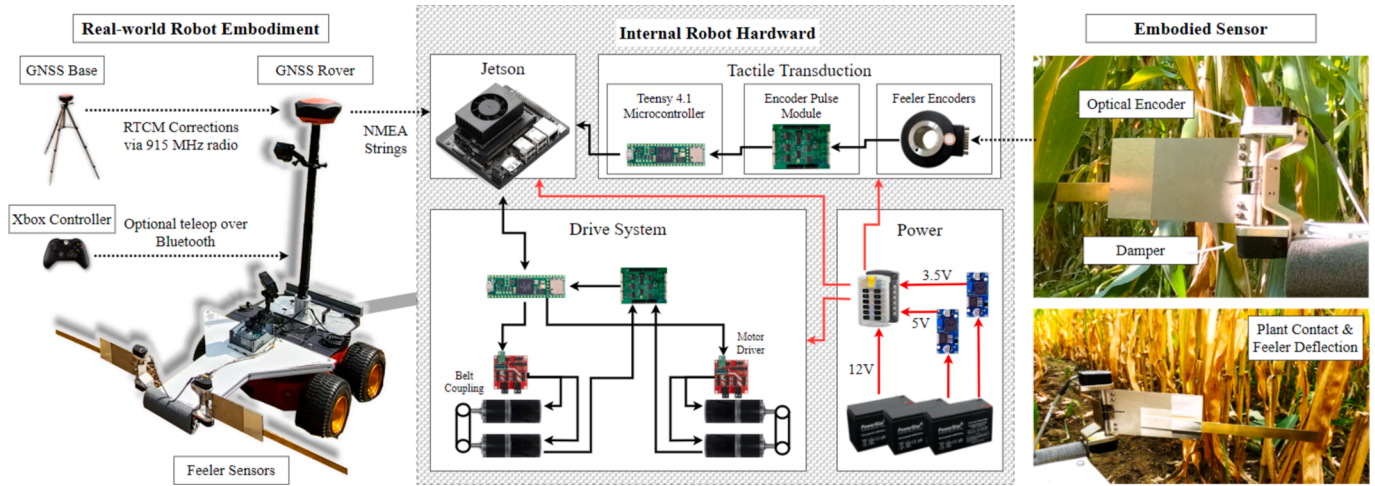


Fig. 13. Real-world UGV Architecture. The system is deployed and tested on a custom differential-drive robot for autonomous navigation in a mature cornfield (~R2). Data from wheel motor encoders, the feeler sensors, and RTK-enabled GNSS are sent to a central chip (colloquially, the UGV's brain), where they are fused for blind spatial awareness, planning, and path execution.

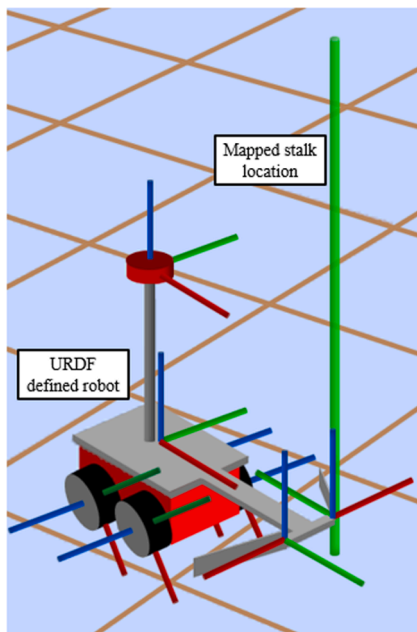


Fig. 14. RViz Model. The robot's understanding of its own state and the environment in exposed using RViz.

on maintaining a centered position within the row alley (so as to not miss stakes) while maintaining a nominal speed of 0.2 m/s and avoiding jerky motion. Whether teleoperated or autonomous, failure to maintain ideal driving impacts the performance of the classification owing to the dynamic relationship between the passive sensor and the vehicle. For example, some stakes are simply missed all together. This occurrence can be caused by false negatives or the sensor simply being out of the range of the stake. Averaging errors in the mapping system can also materialize as false negatives. We observed this occurs when the sensor is heavily deflected from one nearby stake, such that when a second nearby stake comes into range, there is only a small change in the sensor angle while the sensor disengages from one stake to the next. False positives are also shown in the figure, particularly at start-up, where aggressive start-up torque causes the vehicle to jerk, and the passive sensors misidentify contact with an obstacle. This also can also occur because of rapid turns. For the traverse through 249 stakes, we found 5

stakes were either not within the range of the sensor or were completely missed by the teleoperator, 3 stakes were misidentified as being combined with their neighbor due to averaging errors, 4 measurements were false positives corresponding to extra mapped plants, and 8 of the observed localizations were poor, partially due to averaging errors. This corresponds with a real-world detection accuracy of 97.1 % in the analogue environment.

To perform comparisons between the RTK-measured stake positions and the feeler observed positions, false positives and false negatives were identified and the mapped locations were associated with real-world locations according to minimum radial error. The absolute radial error between each measurement and real-world position is calculated using the Haversine distance between the two points, also displayed in the inset of Fig. 16. Between all associated measurements and real-world obstacles, we found a mean absolute radial error of $error_r \cong 0.038$ m. Excluding the qualitative outliers, the value is approximately 0.029 m.

7.2.2. Autonomous navigation in analogue environment

The autonomous navigation system is also evaluated in the analogue environment. The blind vehicle was supplied the goal points shown in Fig. 16 and asked to complete the traverse from one goal to the other, starting with no prior knowledge of the course. Across 50 attempts, we found the vehicle could navigate a mean distance of 22 m down the curved course, with a maximum traverse of 33 m. In summary, the navigation performance of the prototype blind vehicle is remarkably robust and appropriately responsive to obstacles when encountered in a consistent fashion. However, the navigation system becomes brittle following rapid turns due to false positives in the contact state, missed contacts caused by sizeable row gaps that occur within tight local curvature, and the GNSS-fix type transitioning away from an RTK-fixed state, all of which can result in an unrecoverable vehicle state. Position uncertainty is discussed further in Section 8. Additionally, the intrarow spacing in the analogue environment is larger than what might be anticipated in a real cornfield. We observed this occasionally allowed the planned path to erroneously generate between sizeable gaps in a row.

7.3. Navigation in a cornfield

The mapping system and blind vehicle navigation are tested in a real-world, mature (~R2, ~ 3 m tall), production cornfield in Orford, NH. Two reference points were created approximately 50 m apart, centered

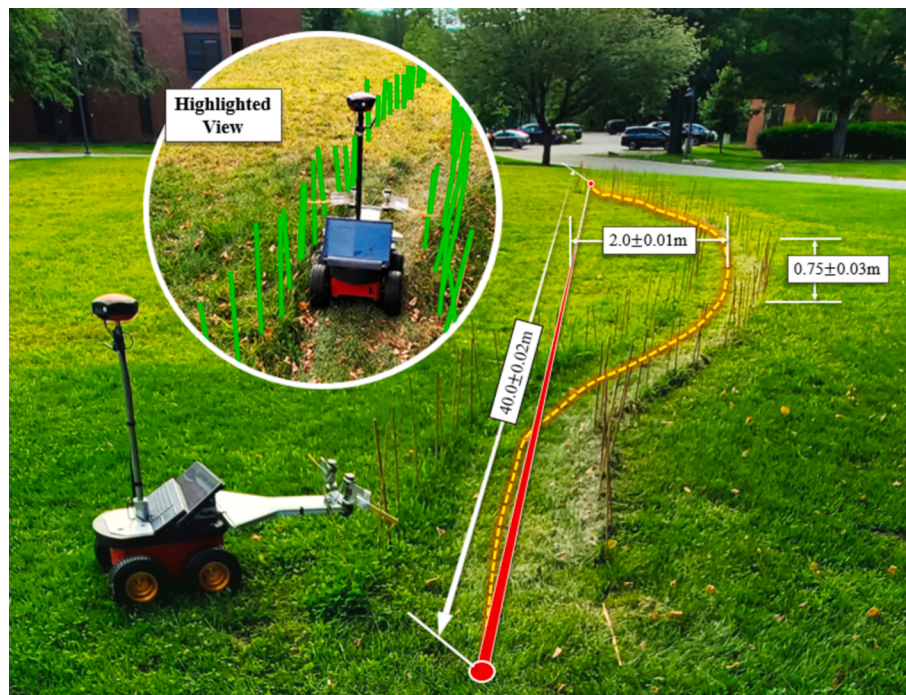


Fig. 15. Analogue Validation Environment. Prior to deployment in a cornfield, the vehicle is evaluated inside of a known environment for validation.

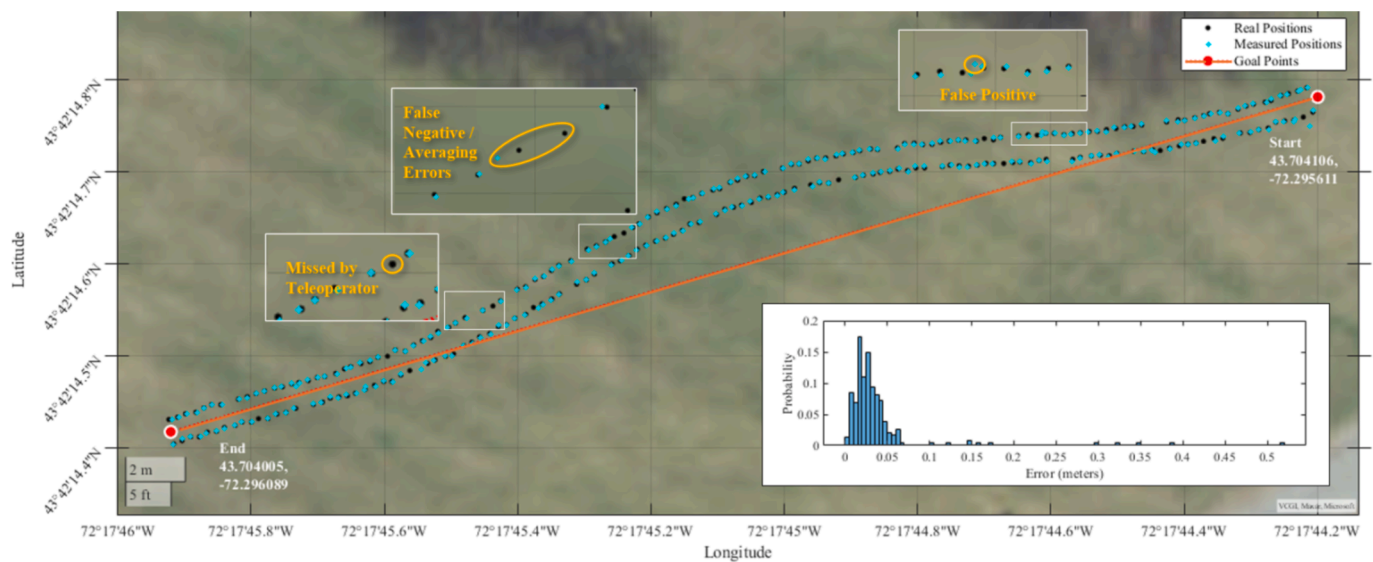


Fig. 16. Validation Results of Localization. The real stake positions as measured via RTK GNSS are compared with the estimated stake location through the eyes of the robot. Key types of classification error, as they materialize from the mapping system, are highlighted and the error in each mapped location is calculated using a Haversine distance.

within a row alley and the vehicle navigated down the row corridor without prior knowledge of the environment. Across 15 attempts, we found the blind navigation system remained robust and successfully traversed a mean distance of 24 m prior to needing intervention. The maximum distance achieved during these tests is approximately 35 m. Various views of the vehicle during these tests are shown in Fig. 17; the stability of the tactile navigation system is demonstrated further in video 1. In general, our observations are similar to that of the analogue environment. The robot tended to travel further prior to becoming unrecoverable than in the analogue environment. We attribute this partially to closer stalk spacing reducing the likelihood of inter-row path planning from the blind-adapted A* node, and the added rigidity of

cornstalks compared to temporary bamboo stakes thus reducing averaging errors.

Loss of an RTK-fix plagues the system seemingly equally in both the analogue and real-world environments. The vehicle is coded to stop should the GNSS lose the RTK-fix, but it may already be unrecoverable before this is registered by the vehicle. Perspectives from the Rviz display are shown in Fig. 18, after the vehicle travelled approximately 32 m, prior to stopping from RTK-loss. One of the central challenges with standard GNSS positioning in this environment is multipath effects and canopy cover, which introduces added uncertainty in the global position measurements. This is shown by the vehicle's understanding of its own position in the figure, shifted west of its own map of the rows, after



Fig. 17. *Blind Navigation in a Cornfield.* The blind navigation system is a novel system sensing modality that can be deployed to assist in navigating through a messy rugged environment, particularly where vision alone is insufficient.

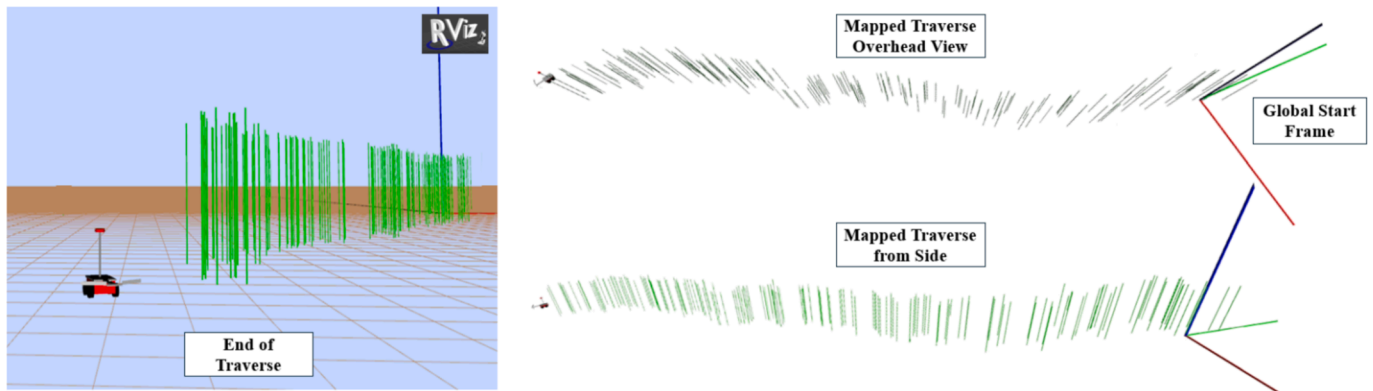


Fig. 18. *Rviz Display of Cornfield Traverse.* The figure displays the vehicle's understanding of its own environment following an autonomous traverse through a cornfield, as exposed to the outside world through Rviz.

losing the fix. Additional work addressing GNSS signal issues is included in [Section 8](#).

8. Discussion

This paper presents valuable insights on utilizing tactile sensors to detect, map, and navigate entirely blind, around stalky row crops like corn. In particular, we claim several contributions to robotic literature on navigation in row-cropping environments: 1.) a novel, passive tactile sensor suited to sense nearby plant stalks. 2.) a simple, heuristic to classify contact with stalks based on the feeler joint state; 3.) an intuitive algorithm to localize detected stalks using only basic trigonometry; and 4.) a proposed method for autonomous robot navigation while blind, using common path planning and path following algorithms. Each contribution is addressed briefly below, using quantitative values to judge performance where appropriate and using qualitative observations where this is not possible.

8.1. Sensor design

This work presents a novel tactile sensor designed to detect and map the environment in row-cropping systems, particularly for navigating among plant stalks like corn. Unlike the systems proposed by [Chen et al. \(2024\)](#) and [Gy and Bajpai \(2023\)](#), which integrate tactile sensors with visual inputs (such as cameras or LIDAR), our sensor relies on a single optical encoder attached to a metal plate to both detect and locate nearby stalks. This design leverages simple mechanical principles to filter out non-rigid obstacles while accurately identifying rigid obstacles such as plant stalks. The passive nature of our prototype sensor introduces unique challenges that have not been overcome entirely, namely false positives in stalk detection caused by high wheel-motor startup torque and rapid turns. Practically, however, the simplicity and scalability of the prototype offers valuable redundancy against leaf occlusion and can [supplement](#) a visual system in local obstacle avoidance.

8.2. Stalk detection

Stalk detection tests in simulation (Section 6.2) and in the analogue environment (Section 7.2.1) both exceeded 97 % accuracy ($(TP + TN)/(P + N)$), compared to the 80 % detection accuracy reported by (Chen et al. (2024) in rice paddy fields and the 100 % and 70 % detection accuracy reported by Gy and Bajpai (2023) to determine hard and soft contacts in cornfields. While the reported value is impressive, it is not indicative of detection accuracy in a real-world cropping environment like Chen et al. (2024) and Gy and Bajpai (2023), because our simulation and analogue environment was void of weeds and leaves. Our vehicle was operated in randomly selected production cornfields making this type of validation difficult; this is reflected in the limited sample sizes for detection testing in the other works. Still, the simulated detection system was tested against simulated vibratory dynamics to reflect the real world, and assessment in the analogue environment directly assesses performance on a real-world vehicle. Qualitatively, detection accuracy does not appear to limit the system in a production cropping environment, as demonstrated in video 1. Also, contact with rigid surfaces by our sensor results in human-discernable signals while contact with flexible features does not. This is why our classifier is a heuristic function, unlike the others, which use frequency response analysis or machine learning for detection.

8.3. Position uncertainty in mapped plants

Stalk positioning is particularly challenging to validate in a production environment, so it is generally evaluated through traversable distances as a proxy. We found from our manual ground truthing in Section 7.2.1 that crop position can be determined to 3.8 cm mean radial error using the tactile sensor. The value is slightly larger, but comparable, to the 1.9 cm mean positioning error found in simulation. This can be contextualized by the estimated uncertainty in a stake position in the global frame (following the approach of Taylor, 1997). In laboratory testing of the obstacle localization relative to the vehicle, i.e., when not subjected to the global transformations and therefore error in global positioning via GNSS, we estimate the radial uncertainty of mapped “stalks” in $\mathbf{M}$ as $\sigma_r \approx 1.0$ cm. The manufacturer’s reported positioning uncertainty for RTK-GNSS is $\sigma_{GPS} \approx 1.4$ cm radially. Finally, we used course-over-ground values from NMEA sentences for characterizing uncertainty of the heading measurement. The measurement uncertainty in course-over-ground values is inversely proportional to the nominal

forward velocity, because course-over-ground is determined based on the change in GNSS position. We found that below 0.05 m/s course-over-ground measurement cannot be used for navigation, because the GNSS position difference is too small; at 0.2 m/s the estimated course-over-ground uncertainty is $\sigma_\theta \approx 10$ degrees, corresponding to a heading-related position uncertainty at the sensor of $\sigma_{\theta r} \approx \sigma_\theta * r = 0.0785$ m, with $r = 0.3$ m. Propagating the uncertainties, an upper bound on stake position uncertainty in the global frame is approximated by

$$\sigma_{\sigma_P} \approx \sqrt{\sigma_r^2 + \sigma_{GPS}^2 + \sigma_{\theta r}^2} = 0.0803 \text{ m (5)}.$$

This relationship roughly demonstrates the trustworthiness of measured stake positions as a function of distance from the GNSS unit, the heading of the robot (and indirectly the forward velocity of the robot), and the type of fix achieved by the GNSS receiver. It is clear that heading uncertainty can dominate this relationship at slow forward travel speeds and concurs with an observed degraded stake position, for example, when the vehicle is turning rapidly but not maintaining a sufficiently high forward rate of travel.

8.4. GNSS performance Under-the-Canopy

GNSS signals are crucial for determining the location of nearby stalks, whether by vision or touch. Signal blockage of satellites (SVs) by leaves and multipath effects are known causes of degraded GNSS positioning and are cited as sources of difficulty for UGVs operating within a row alley (Johannessen, 1997, Manish et al., 2021; Sivakumar et al., 2021). However, GNSS performance is not well-characterized in this context. To characterize GNSS operability in this environment in greater detail, the test UGV was used to gather geolocation data from the mobile receiver along a pre-planned, unmodified path in a mature corn field ($\sim R1$, ~ 3.2 m tall). Mast height was varied to characterize the quality of the positioning data when gathered 3.66 m, 2.44 m, 1.37 m, and 0.46 m from the ground (~ 0.46 m above the canopy, and ~ 0.76 m, ~ 1.83 m, and 2.74 m below the top of the canopy, respectively). The respective heights were selected to represent measurements from above, inside, at the base of, and near the floor of the canopy.

8.4.1. GNSS positioning

Position estimates from the receiver, at various mast heights relative to the canopy, are shown in Fig. 19a. The data taken from above-the-canopy, inside-the-canopy, and below-the-canopy maintained an RTK-fix via RTCM corrections over radio along the duration of the traverse and are positioned along the row alley. Radio corrections could not be

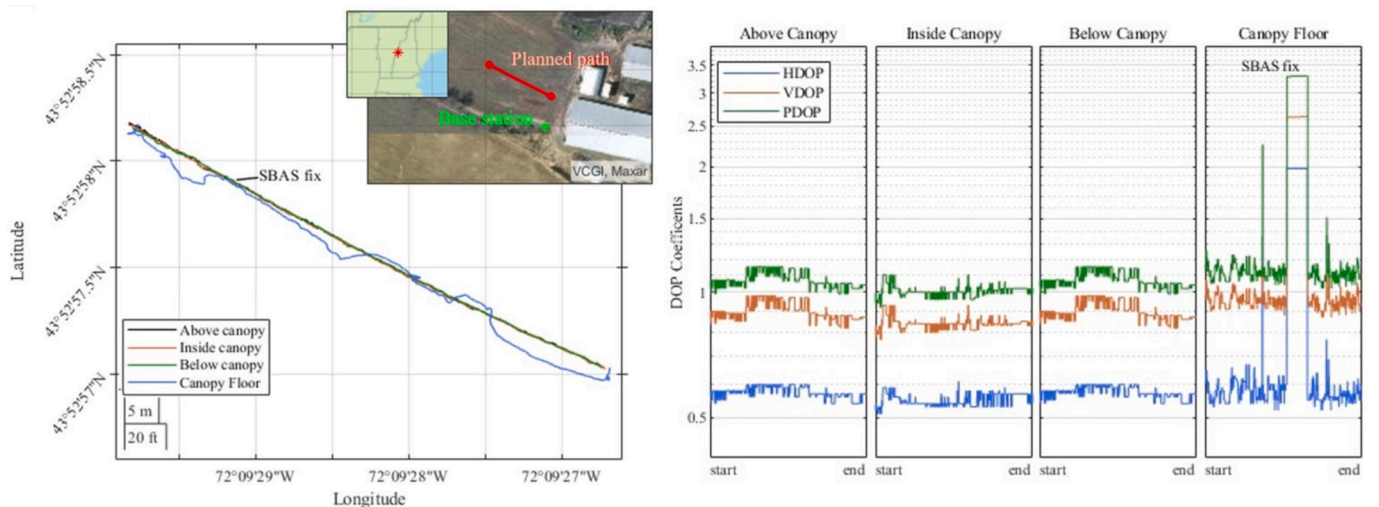


Fig. 19. Performance of Multi-band GNSS for Varying Canopy Cover. (a) All runs in which an RTK-fix was maintained, positioning performance remained within the row, while loss of RTK functionality and row-centered positioning was experienced close to the canopy floor. (b) Dilution of precision was assessed across the traverses at varying mast heights to investigate the effects of increased canopy cover on the performance of modern multi-band GNSS systems.

Table 2
Multi-band GNSS Performance of Receiver Relative to Canopy Cover.

Receiver Location	Fix Type / Quality	DOP	HDOP	VDOP	PDOP	SVs in View	SVs in Fix	C/N0
Above Canopy	RTK-fixed	0.57	0.89	1.06	31	27	40.97 ± 5.80	
Inside Canopy	RTK-fixed	0.54	0.84	1	31	27	38.89 ± 6.76	
Below Canopy	RTK-fixed	0.57	0.89	1.06	31	26	33.97 ± 8.98	
Canopy Floor	Auton.-fix	0.57	0.97	1.12	30	25	21.74	
	SBAS-fixed	1.98	2.64	3.30	30	25	± 7.89	

received across traverses taken with the receiver near the canopy floor leading to a degraded position fix along the traverse. Near the canopy floor, an autonomous-fix was maintained along the majority of the traverse, and during a brief window, also shown in Fig. 19, a satellite-based augmentation system (SBAS)-fix was achieved, during which the position estimate recentered along the row alley for ~ 14 m. SBAS improves the accuracy and reliability of GNSS signals by broadcasting corrections over the coverage area of geostationary augmentation SVs.

8.4.2. Dilution of precision

Dilution of precision (DOP) coefficients were investigated to assess signal integrity across the heights during these traverses, presented in Fig. 19b. DOP values characterize the variance of GNSS observables; lower values are generally interpreted as higher SV coverage. Median values of HDOP (horizontal), VDOP (vertical), and PDOP (3D position) are shown in Table 2. Elevated DOP occurred during the SBAS-fix window in the canopy floor run, indicating the corrections were provided to correct for momentary weakening of the satellite and receiver geometry. Expectation from the literature is that HDOP becomes elevated as the receiver descends into the canopy, however geometric precision does not appear to dilute with increased canopy coverage, as median DOP values remains consistent across receiver heights.

8.4.3. Signal continuity and strength

SVs information, fix type, and mean carrier-to-noise power spectral density (C/N0) were used to assess signal continuity and relative strength, also summarized in Table 2. C/N0 estimates from every SV in view at every timestep, for each traverse, are organized into 50 bins across dB-Hz levels and normalized to understand C/N0 as a function of

canopy cover in Fig. 20a. While the geometric quality of signals does not appear to drop off, C/N0 decreased as the receiver is lowered into the canopy, indicating a drop-off in signal strength as overhead leaf coverage increases. Variance in this ratio also increases as canopy cover increases. The number of SVs does not appear to drop off substantially with increased canopy coverage, even absent an RTK-fix, but as overhead obscuration increases the band of SV elevation angles cut-off from reception widens, as shown in Fig. 20b, with sizeable cutoff bands from 61 to 81 degrees for traverses below the canopy and near the canopy floor.

8.4.4. Speed over ground

Tradeoffs exist with performing GNSS positioning higher in the canopy. Drop off in carrier strength at lower canopy heights is accompanied by GNSS derived estimates of robot speed over ground that more closely match odometry estimates derived from wheel speeds, as shown in Fig. 21. Data taken from higher in the corn leaf canopy results in elevated GNSS speed over ground. Because the mast is long, flexible, and its center of mass is further from the attachment point, the mast whips violently as the vehicle progresses along the traverse, increasing the magnitude in the receiver speed estimate. In the field we also observed taller masts becoming caught on the top of corn stalks, further increasing this whipping effect as the mast overcomes static friction and returns to a central position. Our results show that low-cost, multi-band, RTK positioning performance is consistently of a high enough quality for estimation from within a row alley, nearly irrespective of receiver height, so long as an RTCM corrections (and therefore the RTK-fix) can be maintained consistently.

8.5. Autonomous distance prior to intervention

Finally, the ability to plan and execute a planned path while blind can be evaluated quantitatively against existing under-the-canopy navigation research. In simulation, we found a robotic vehicle could travel a mean distance of 35 m down a curved, gap-laden, cornfield and 65 m down a straight, gap-laden row alley with just two feelers. Additionally, the maximum autonomous distance in simulation was more than 100 m with two feelers and curved, gap-laden rows. In the real-world production cornfield with curves and gaps, we found the prototype vehicle could autonomously travel 24 m on average and a maximum distance of 35 m prior to needing intervention. For comparison, in manicured, gap-free fields, Velasquez et al. (2022) reports a maximum distance of 386.9 m using a camera, LIDAR, and IMU; and Sivakumar et al. (2021) reports

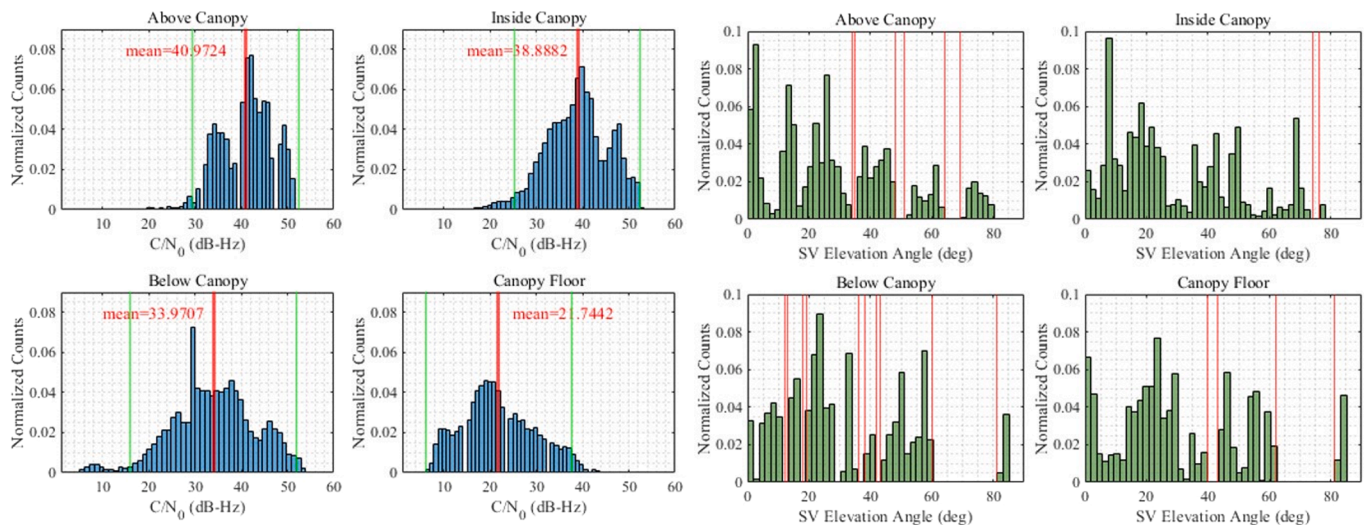


Fig. 20. C/N0 and Signal Blockage as a Function of Canopy Cover. (a) Signal strength decreases with increasing canopy cover. (b) Cut-off angles directly overhead widen as the receiver descends below the canopy.

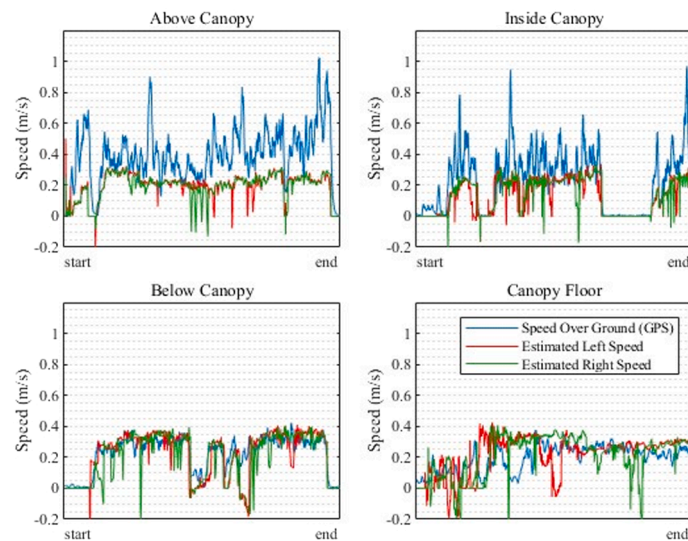


Fig. 21. Speed Over Ground as a Function of Canopy Cover. Being elevated in the canopy induces whipping effects that lead to errors in speed over ground estimates, making the data unusable for odometry. This reduces the shorter & less flexible the GNSS mast becomes.

485 m using a camera and IMU, both using machine learned approaches. Elsewhere, Velasquez et al. (2022) claims an average distance of 47.5 m, and Sivakumar et al. (2021) claims an average distance of 100 m (without the IMU) in production fields with gaps. While we make no claim of superiority over the performance of these visual system, the length of autonomous traverses using our first-of-its-kind tactile approach in an unmanicured field is on the same order as what is presently achievable using fused-visual approaches despite being entirely blind. This indicates the potential value of incorporating novel tactile sensors into future work on under-the-canopy navigation, both for detection of nearby stalks and local obstacle avoidance while visually-impaired.

9. Conclusion

Unconventional N fertilization strategies, particularly high-frequency spoon-feeding, show promise in enhancing crop yield while reducing fertilizer requirements. Our crop study findings underscore the potential positive impact autonomous UGVs could have to pave the way for more sustainable and efficient crop management systems. To unlock new, more efficient precision methods in row-crop agriculture, advancing the autonomy of small UGVs is essential. Presently, sensor occlusion, lighting variation, and computational load burden visual navigation in row-crop environments. Our contribution demonstrates a novel obstacle detection approach to mapping these complex, structured environments using only tactile inputs. Through a simple sensor that mechanically filters non-rigid obstacles from rigid ones, combined with intuitive algorithms, we can extract spatial information about nearby plants from the joint state of a single encoder. This system achieves high-fidelity global position accuracy of mapped plants, with a radial error of < 2 cm in simulation and < 4 cm in the real world. We have also demonstrated the viability of blind, autonomous navigation in a corn-field using common path planning and following algorithms. The system covers more than 100 m in simulation and 30 m in real-world cornfields before requiring intervention. It overcomes challenges like high row curvature, planting gaps, dense weeds, canopy cover, and variability in planting patterns—without any vision or ranging system. In the future, the simple methods discussed here can be refined to push the boundaries of navigating while blind. Likewise, they may be leveraged to supplement visual-centric navigation modalities to provide system redundancy against visual impairment, enhance the performance of interplant

manipulators and row-guidance systems, and produce higher-fidelity automated systems in agriculture. As the performance of these small, autonomous vehicles improves, a plethora of yield enhancing and input-cost saving management tasks, like spoon-fed fertilization, may be investigated further. Overall, this paper contributes valuable insights into the design, operation, and optimization of single-row UGVs for precision agriculture and offers meaningful insights into non-visual sensing techniques. By addressing key challenges and proposing innovative solutions, we aim to catalyze further research and development in this burgeoning field, ultimately fostering sustainable agricultural practices to enhancing food production.

CRedit authorship contribution statement

Adam M. Gronewold: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Philip Mulford:** Writing – review & editing, Investigation. **Eliana Ray:** Investigation. **Laura E. Ray:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Laura Ray reports financial support was provided by National Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.].

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.compag.2025.110003>.

Data availability

Data will be made available on request.

References

- Lance Gibson of Corteva Agriscience is providing technical insights into the development of corn and the efficacy of existing management technologies. The generosity and knowledge by all have improved this study in innumerable ways. This work was supported by the National Science Foundation under grant number 1824687 and a PhD Innovation Program Fellowship from Dartmouth College.
- ## Appendix A. Supplementary data
- Supplementary data to this article can be found online at <https://doi.org/10.1016/j.compag.2025.110003>.
- ## Data availability
- Data will be made available on request.
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