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Towards Agricultural Robotics for Organic Farming *

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Abstract
In big scale agricultural farming complex machines with advanced technology shape already the daily routine. In opposite, the field of organic farming is still characterized by multiple manual tasks that include heavy labor. Our vision is that the fields of automation and robotics offer the necessary technology to lift the burden of back-breaking work off the worker's shoulders. Hence, we propose a scalable and modular agricultural robotic concept that advances farming to the next higher technology level. We provide a low-cost and flexible design in order to realize different autonomous applications, specialized for light weight agricultural work. As proof of concept the proposed configuration is integrated and validated as the experimental platform FRANC. All experiments are performed in real-life outdoor scenarios as vegetable fields that are sowed or planted in row structures. Therefore, we utilize a local navigation system based on a self-parameterizing crop row detection, that enables a local, adaptable, and GPS-independent navigation. The tests show that the hardware and software of the designed system is able to handle rough terrain, offers a high maneuverability, and is adaptable to different row-structures.

1. Introduction

Within the last decades new automation technologies, industrial robots and sophisticated automation machineries entered the food production chain and led to a higher efficiency and increased the productivity of the harvesting process.

Sensors and software that transform classic agricultural machineries into semi-autonomous systems are already available on the market [11]. We belief that robotics has the ability to advance this semi-autonomous systems to the next higher technological level and promises to answer the question how the production chain can be fully automated in each single step of the food production, starting already at the cultivation of the crops. Therefore we developed a scalable, and modular agricultural robotic systems suitable to better support light-weight agricultural work.

As stated by [17], one way to increase the economic efficiency in future crop production may be done better and cheaper with a swarm of small machines than with a few large ones. By the means of our modular concept re-designing existing solutions can be avoided and it becomes possible to enhance existing solutions with robotic modules, for instance a conventional finger cultivator can be turned into a robot by attaching the respective robot module.

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Figure 1: Experimental platform and proof of concept FRANC.

In this article we present our modular system design and concepts for more flexible agricultural robots as well as its realization with the platform FRANC (cf. Fig. 1) as proof of concept. Our contributions are (i) a modular robotic system concept that (ii) can be use for the robotizing of existing farm facilities and (iii) a generic row detection algorithm that does not need any a-priori information. Moreover, we present field trial results of its performance on vegetable fields.

2. Related Work

Most of the state-of-the-art agricultural automation systems are either focused on the (semi-) automation of big land machines or support the farmer during different field manipulation procedures with additional sensor information [11].

Research groups robotized already "standard platforms" as golf carts or other small scale vehicles to focus on algorithms and sensor technologies without the need of the re-development of the grounding vehicle [16, 10, 5]. Contrary there are also completely designed robotic systems such as BoniRob which are suitable for highly specialized solutions as occur in the area of precision farming [3]. As described in [3] BoniRob Apps are comparable to the classical implements. These Apps can be directly integrated on the robot. Existing agricultural machineries have to be redesigned if they have to be used be used with the robot. However, we aim to develop a solution which can be used in combination with existing implements and farm facilities, with little or no additional product development needed.

The contribution presented in this article is a system design concept that sets out to close the gap of existing agricultural robotic systems: rather than focusing on one large multi-purpose autonomous machine, we offer a flexible solution for cheaper crop row production which might be even more acceptable for smaller farms as it allows robotizing existing machines. We present our contribution in the form of a detailed system description and the results of preliminary field trials. Our results should help other researchers and engineers to solve the existing challenges in agricultural robotics with respect to development of robotic systems for light-weight agricultural work.

3. Approach

We approach a robotic system, including a row guidance an autonomy module that adapts by itself to any kind of row organized fields. Our concept includes individually replaceable subsystems that will be presented here.

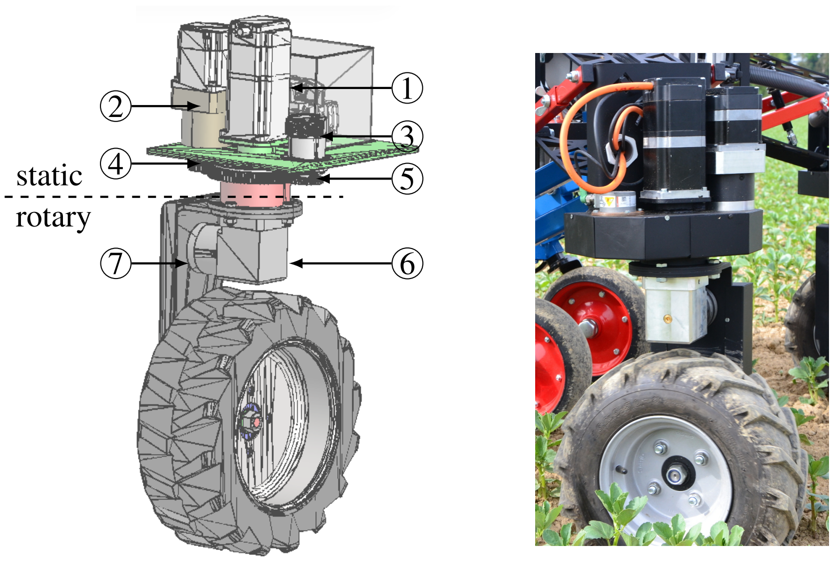


Figure 2: Mechanical realization and parts of the powertrain. ① drive motor and break, ② steering motor, ③ powertrain electric, ④ steering gear, ⑤ optical absolute rotary steering encoder, ⑥ 90° gear, ⑦ chain drive.

3.1. Mechanical Realization of the Powertrains and n-Wheeled Drive Kinematics

As each car-like vehicle, the robot needs at least three degrees of freedom (DoF). The classic kinematic realization of service robots are differential drives, in opposite we decided to implement a n-wheeled steering to combine tractive power, maneuverability, and scalability of the robot. Hence, we propose a kinematic encapsulated powertrain that can be equipped with or without a motor for the steering or tractive power. The wheel can be realized as free running wheel without any motor, can be equipped with a single motor for pure tractive power, or as fully powered, independent steerable wheel (cf. Fig. 2).

Most of the already realized systems use wheel hub motors [2, 3]. Wheel hub motors need a wired connection from the static part to the rotary part. That connection constrains the number of possible wheel turns respectively the maximum steering angle and makes the inverse kinematic complex, because the algorithms have to consider the prior steering motions. We approach a cable free rotary part that allows infinite wheel turns in order to remove these constraints for the trajectory planing.

Vehicles that are equipped with more than one steerable wheel, need a interconnected steering that fulfills the Ackerman-constraint [4]. Summarized, the perpendicular line of each wheel has to intersect at one point. However, pure mechanical realizations of steering systems go hand in hand with comparable complicated mechanical constructions. Hence, we replace the mechanical connection by a electronic connection and an intelligent control that is able to handle the steering maneuverer independent from the amount of steerable wheels, based on their position in the kinematic constellation. Based on the Ackerman-constraint and the "instantaneous center of curvature" $\mathbf{P}_{\mathrm{ICC}}$, the necessary steering angle θ_n and different velocities v_n of the single wheels can be calculated with (1)-(4c). The approached equations result automatically in valid trajectories and steering angle configuration if $\mathbf{P}_{\mathrm{ICC}}$ is linearly interpolated. Figure 3 depicts an exemplary kinematic configuration and depicts the nomenclature used for the equations. Different drive behaviors for different in field use cases as a pure back or front steering can be realized dependent on the position of $\mathbf{P_{ICC}}$. The virtual coordinate system $[\mathbf{x_V}, \mathbf{y_V}]$ is used to shift the zero position and the privileged direction.

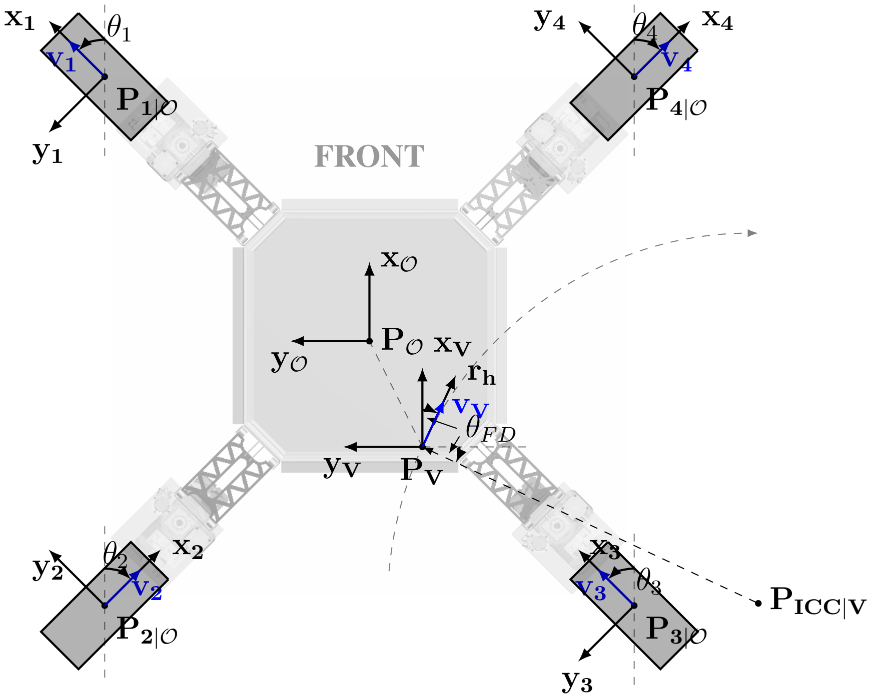


Figure 3: Exemplary kinematic configuration with four independently steerable wheels.

$$\theta_{FD} = \mathrm{atan2}\left(\mathrm{P_{ICC,x}} + \mathrm{P_{V,x}}, -\mathrm{P_{ICC,y}} - \mathrm{P_{V,y}}\right) \tag{1}$$

$$P_\alpha = (P_{ICC,x} + P_{1,x})^2 + (P_{ICC,y} + P_{1,y})^2 \tag{2}$$

$$P_{n,a} = (P_{ICC,x} + P_{V,x}) \cdot P_{n,y} - (P_{ICC,y} + P_{V,y}) \cdot P_{n,x} \tag{3a}$$

$$P_{n,b} = (P_{ICC,x} + P_{V,x}) \cdot P_{n,x} + (P_{ICC,y} + P_{V,y}) \cdot P_{n,y} - P_\alpha \tag{3b}$$

$$\theta_n = \mathrm{atan2}\left(\mathrm{P_{n,a}}, \mathrm{P_{n,b}}\right) + \theta_{\mathrm{FD}} \quad , \tag{3c}$$

With θ_{FD} as the forward direction, $\mathbf{P_{ICC}}$ as the instantaneous center of curvature, $\mathbf{P_v}$ as the origin of the virtual coordinate system, $\mathbf{P_n}$ as the position of the wheel in the kinematic configuration, and $\mathbf{P}_\alpha, \mathbf{P}_{n,a}, \mathbf{P}_{n,b}$ as auxiliary variables. The speed of the single wheels can be calculated based on the distance of the origin of the wheels $\mathbf{P_n}$ to $\mathbf{P_{ICC}}$ with (4a)-(4c).

$$r_n = |\mathbf{P_{ICC}} - \mathbf{P_n}| \tag{4a}$$

$$r_{max} = max(r_n) \tag{4b}$$

$$\mathbf{v}_n = \mathbf{v}_m \cdot \frac{r_n}{r_{max}} \tag{4c}$$

with v_n as the speed of the n^{th} wheel and v_m as the intended maximum speed of the fastest wheel.

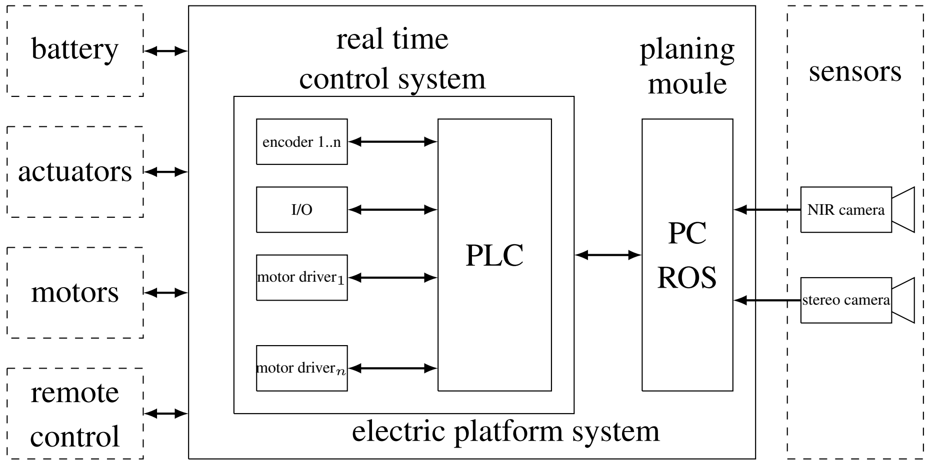


Figure 4: Electrical platform system and the adjacent systems.

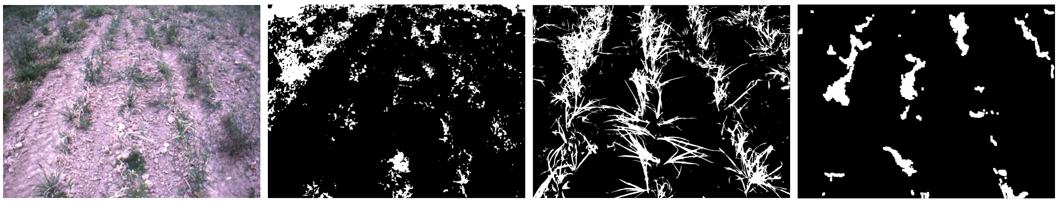
3.2. Electronics and Control System

The vehicle electronics is the bridge between the robot kinematic, including the motors, and the autonomy and row guidance software. Figure 4 shows an overview of the system parts. The necessary sensors system is closely connected to the implemented row guidance system. Based on the review of the prior work [13, 11] we consider that vision systems provide the information for an adaptable navigation and in field task execution. Hence, we approach a vision system that observes light within different ranges of the electromagnetic spectra and is mounted on the robot front. The sensor system consists of two stereo cameras and a NIR camera. A NIR pass filter and the sensitivity of the built in chip form in combination a band pass filter that enables a detection of light from 850nm to 1000nm.

3.3. Row Guidance and Autonomy Software

The row guidance system consists of a segmentation step, followed by a detection of the rows and a parameter extraction. The images are segmented based on NIR and depth data that are provided by the camera system [7]. The extraction of the height information is realised with an online plane calibration that allows determining the camera pose relative to the estimated ground plane.

Several machine vision based row guidance approaches [1, 8, 12] consider pure RGB or NIR information for the segmentation of the plants and soil, while 3D information is omitted and the other way round [9, 14]. Pure RGB-data-based segmentations often fail to segment crops from the soil if they stopped already the production of chlorophyll and lose their green color, while NIR light is still reflected by the cell structure of the leaf (cf. Fig. 5 (b) and (c)). Otherwise, a pure height-based segmentation fails e.g. in early growing stages of the plants, the spectral information can be used as soon as small plants are visible. We approach in [7] a segmentation that fuses both, NIR and depth information together and utilizes the advantages of the one method to compensate the shortcomings of the other. The height information improves the results especially for fields where plants are sowed on dams and allows to filter out small plants and weeds that would add noise to the segmented image (cf. Fig. 5 (d)). Further, the available 3D information enables a projection of the segmentation result to the online estimated ground plane and enables a height-bias-free crop row detection. The row guidance system detects the rows based on a geometric row model and a particle-filter-based row parameter estimation as approached in [7]. The row model describes with three parameters a parallel pattern of lines in the 2D space. The first two parameters α and p represent the 2D normal vector $\mathbf{p}$



(a) (b) (c) (d)

Figure 5: Comparison of different segmentation methods. (a) RGB image, (b) 2G-R-B segmentation [15] , (c) NIR segmentation, (d) NIRD segmentation. (a), (b), (c), and (d) show the same scene under different field of views.

of the closest line and points to the origin of the coordinate system. The third parameter is the scalar d which describes the distance between the lines of the repetitive pattern. The filter samples a 3D parameter space with N hypotheses. Each hypothesis is weighted based on the segmented image. In opposite to other methods the approached crop row detection does not need any prior information on the row structure. Moreover, the particle-filter-inherent properties in combination with the selected geometric row model enable a tracking of the crop rows and improve the results even and especially if natural row irregularities occur. Finally, the negotiable track is extracted out of the row information and is further filtered and processed for the steering information. To achieve the modularity of the whole system, the row guidance is wrapped in the robot operating system (ROS) and can be replaced by another guidance system if necessary. In our recent work we have investigated in [6] how the fusion of odometry and row guidance information can improve the detection results.

4. Tests and Results

As proof of concept we built with the developed subsystems the robotic platform FRANC (cf. Fig. 6). It consists of a frame that carries the electronic and sensor system and is powered with four independent steerable wheels. The algorithms, controller, and the security concept including the remote control with the emergency stop function were implemented to form a whole system with minimal effort.

As stated by [13] the integration task can be a significant effort on its own. The modular concept reduced the integration of the single modules into an overall system to a few mechanical engineering steps as the preparation of the frame including the mounting points and an one-time parametrization of the electrical system and the control algorithms. The parameterizable and adaptable algorithms and interface design simplifies the integration of the subsystems into a working solution and overcomes several integration problems that have to be faced in traditionally designed systems.

FRANC was successfully tested in rough terrain and recorded in-field data for the evaluation of the row guidance algorithm that is used by the autonomy software. The tests proved the feasibility, maneuverability, and rigidity of our modular concept for real-life applications.

The crop row detection algorithm and row guidance software is tested with data recorded during in-field tests of the robot. The robot was maneuvered within row organized fields, parallel to the rows. With this information, parameter windows for p and α can be defined to evaluate the crop row detection algorithm. Correct row structure estimations have to end in a parameter configuration that describe rows within the given windows. Since the row distance has to be constant during the whole procedure, the error of the row distance estimation e_d is directly determined based on manually measured ground truth data. The particle filter is initialized with $N = 1000$ randomly generated hypotheses that represent parameter configurations with $\alpha = \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$, $p = [-0.75\text{m}, 0.75\text{m}]$, and $d = [0.2\text{m}, 1.5\text{m}]$.

Figure 6: FRANC during in-field trials.

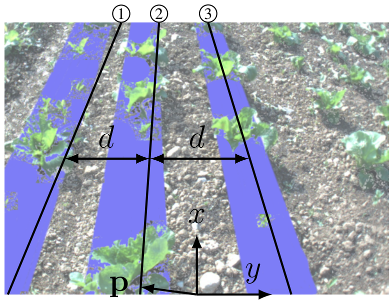


Figure 7: Crop rows and parameter windows.

The parameter windows are defined with $p_w = [0.2\text{m}, -0.2\text{m}]$, $\alpha_w = [+0.2\text{rad}, -0.2\text{rad}]$, and the manually measured ground truth data for the row distance $d_{GT} = 0.45\text{m}$. The experiments show that the particle filter based crop row detection ends in average after five cycles in correct estimations for all three parameters (cf. Fig. 8). The steps within the row offset can be ascribed to the normalization algorithm that searches for the closest line of the pattern to the origin of the coordinate system that was slightly shifted to the right side during the recordings. Hence, the orientation and the offset of the row pattern is either described with line ② or ③ (cf. Fig. 7).

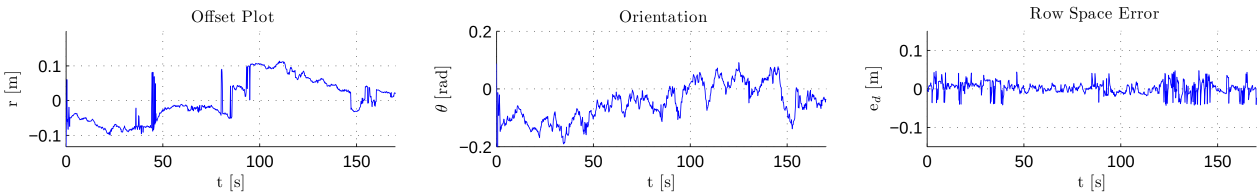


Figure 8: Results of the row detection algorithm with data recorded during in field trials. Offset and orientation has to be within the windows as stated in the text. Average error of the row distance parameter refered to the ground truth.

5. Conclusion

In this article we presented a design concept for a modular agricultural robot and its realisation in the FRANC prototype including results on preliminary field trials.

Testing FRANC in the field proved its maneuverability on rough terrain. The recorded in-field data for the evaluation of the row guidance algorithm revealed that the particle-filter-based crop row detection ends in average after five cycles in correct estimations.

We believe that the conceptual design, its prototypical realization, and the preliminary field trial results presented in this article constitute valuable knowledge for fellow researchers in the field of agricultural robotics and serve as a stepping stone towards developing robotic modules for more flexible agricultural automation.

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