A multilevel simulation framework for highly automated harvest processes enabled by environmental sensor systems

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Abstract

This article proposes the concept of a simulation framework for environmental sensors with multilevel abstraction in agricultural scenarios. The implementation case study is a simulation of a grain-harvesting scenario enabled by LiDAR sensors. Environmental sensor models as well as kinematics and dynamic behavior of machines are based on the robotics simulator Gazebo. Models for powertrain, machine process aggregates and peripheral simulation components are implemented with the help of MATLAB/ Simulink and with the robotics middleware Robot Operating System (ROS). This article deals with the general concept of a multilevel simulation framework and in particular with sensor and environmental modeling.

1. Introduction

Extensive field tests are necessary to represent the diversity of possible constellations in environment-based functions and cooperative processes in agriculture. Due to harvesting periods, such tests are only possible to a limited extent and there are rarely ideal conditions for testing function thresholds. Measurements depend on a variety of environmental disturbances and in particularly harvesting tests cannot be reproduced. Environmental models can support the development process of machine control functions that are based on environmental sensing [1]. The development process of advanced driver assistance systems (ADAS) in automotive uses frameworks for simultaneous vehicle dynamics, drive train and environmental sensor simulation for reducing the number of time- and cost-intensive vehicle tests [2]. However, agricultural harvest scenarios require more complex machine and environmental models, since the steering and longitudinal guidance as well as machine cooperation rely on the harvesting process prior to navigation. An appropriate mapping of plants and soil, yield parameters, possible further process participants and obstacles is necessary. As ADAS development tools are optimized for vehicle, sensor, and environmental models for cars, they need substantial modification for being suitable for agricultural off-road scenarios. This article proposes the concept of a multilevel simulation framework that is suitable for agricultural harvest scenarios, thereby including control functions, sensor integration up to machine cooperation.

2. Materials and Methods

2.1 Multilevel Simulation

Since environmental automation functions are often interdependent with other functions or process participants, the simulation has to serve several function levels (fig. 1). Through the requirements of model-, software- or hardware-in-the-loop test scenarios and with regard to limited resources, simplified models for partial functions that do not require supervision can be chosen. On the other hand, it is also possible to isolate individual simulation components.

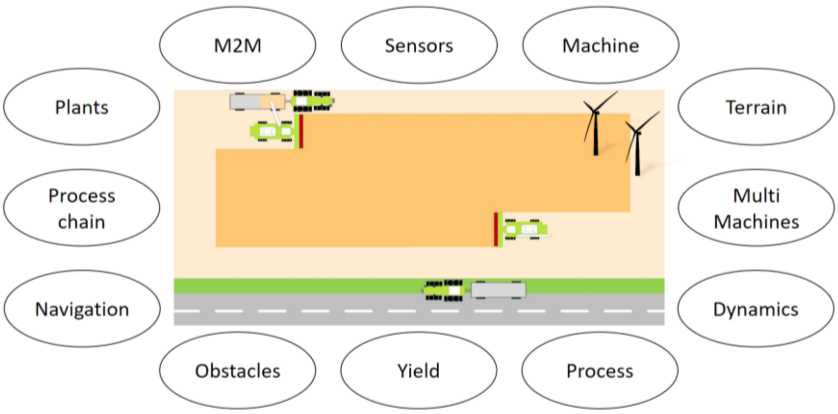

Fig. 1: Levels for multilevel simulation environmental automation functions

2.2 Simulation Framework

In order to provide the greatest possible flexibility in environmental modeling and implementation of own sensor concepts, the open source robotics simulator Gazebo [3] is chosen in this work. It offers a wide range of available and fully exposed sensor models and an Open World scenario simulation which is generally suitable for agricultural scenarios [4]. Another main component of the simulation framework is MATLAB/ Simulink [5], which serves as an interface to the previous development process and allows the use of many already existing model components, including models for powertrain, suspension and process simulation of a harvesting machine. Message transport between Gazebo Simulation and

MATLAB/ Simulink uses the middleware ROS [6], based on a publisher-subscriber or service based interaction model. An implementation example is the well-known LiDAR-sensor-based steering control by crop edge detection in harvest (fig. 2).

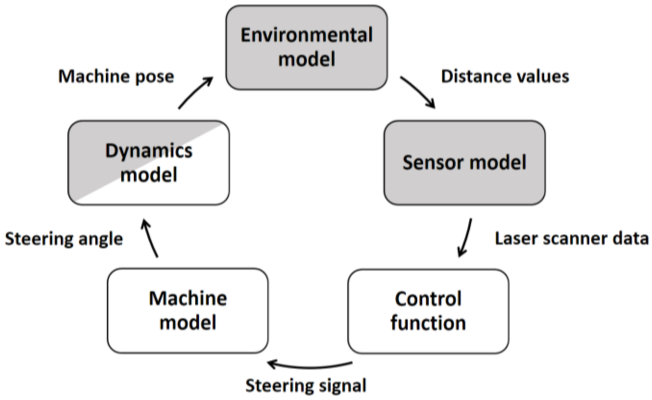

Fig. 2: Flow chart for a LiDAR-sensor-based steering control simulation with model parts in Gazebo Simulator (grey area boxes) and MATLAB/ Simulink (white area boxes)

2.3 Environmental Model

The environmental model holds an environmental representation on which field-related sensor data can be generated. These include soil, crop, stationary objects, and vehicles.
The environment has to be represented in a way so that it is suitable for multiple environmental sensor systems. These include environmental sensors such as LiDAR, camera, and radar sensors, as well as GPS, IMU and odometry sensor systems. Access to stored map related data of the surroundings as an additional virtual sensor is also possible. All components are represented by a 3D contour such as the soil topography or the 3D machine representation. The terrain topography can be described by means of measured values from previous measurements (or mathematically), texturing for vision sensors or speed-dependent crop mass flow are possible.

2.4 Environmental Sensor Systems

The environmental sensor models relate to the respective machine position and form the interface between environmental simulation and vehicle function. The modeling is carried out by experiments based on measured values. The possibility to implement new machine and function concepts as well as sensor systems and other plant species will be discussed in the further course of the project. For the LiDAR sensor simulation, three different model approaches for the generation of sensor data output were implemented in the sense of scalability (fig. 3). For real-time capability there is no physics simulation of laser pulses, beam deflection or time-of-flight but a phenomenological behavior simulation based on the preexisting GPU accelerated ray casting plugin of Gazebo. The first approach is a position-dependent reproduction of measured data instead of route models. Real sensor data from field tests are first transformed to a plant height and located in a grid. It is possible to replay a real measurement but with the possibility of slightly different trajectory and variable speed to represent an active control for function stability consideration. This approach can also be extended by the use of primitive bodies to reflect the effects of shading at crop edges.

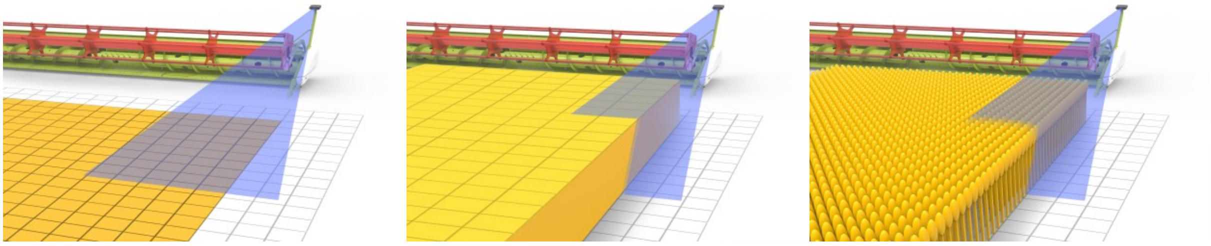

Fig. 3: Sensor model concepts

The second approach is to use primitive bodies together with empirically determined sensor parameters. The height and number of plants influences a laser distance measurement. Sensor properties, such as the spot size, have a strong influence on the measured height [7]. This sensor-specific behavior can be described by parameters such as the standard deviation of the distance measurement in known crop conditions and modeled as a function of the height and the number of plants. The third approach is based on full generic sensor data by a 3D-surface plant model of individual plant contours without prior measurement. The realization of multiple types of plant stocks is possible. For this purpose, a simplified plant contour model and a matching sensor model was developed. For a more realistic sensor behavior, a plurality of individual distances according to the ray casting principle are combined to form a measurement as a function of the desired measurement spot size. According to the desired sensor behavior, both the smallest distance values, but also any percentiles of the measured distance values, can be selected for determining the output distance value. The choice of the sensor representation depends on detail and performance requirements of the application. The generation of measurement data can be deterministic or stochastic. In addition generic sensor data extracted by this 3D-surface plant model can provide input for one of the other model approaches in order to gain a performance profit.

3. Application Example

An exemplary implementation and validation is based on LiDAR-based edge detection as an established environment-based function in grain harvesting. This example is intended to test the basic concept and the interplay of the individual software components on the basis of an existing concept. To generate sensor data for model parametrization and validation real field models have been built with different crop densities (fig. 4) as a first step. Those models have been measured using two high resolution laser scanners with different beam sizes.

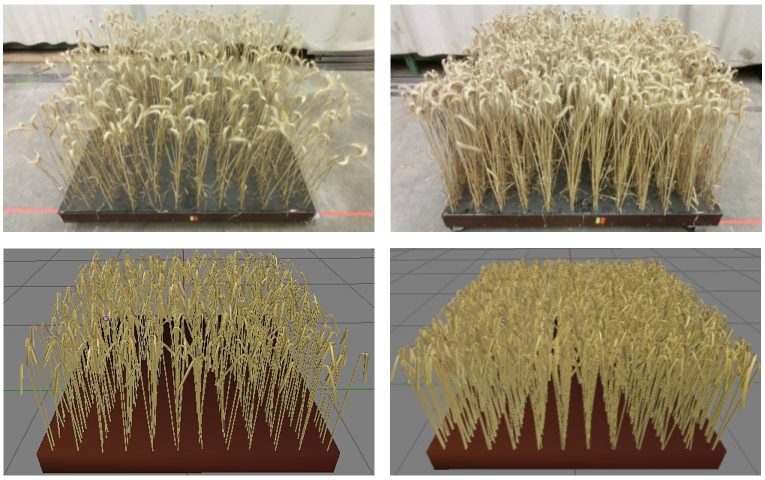

Fig. 4: Real model (top) and 3D-surface model (bottom) of 200 (left) and 600 (right) crop plants per square meter

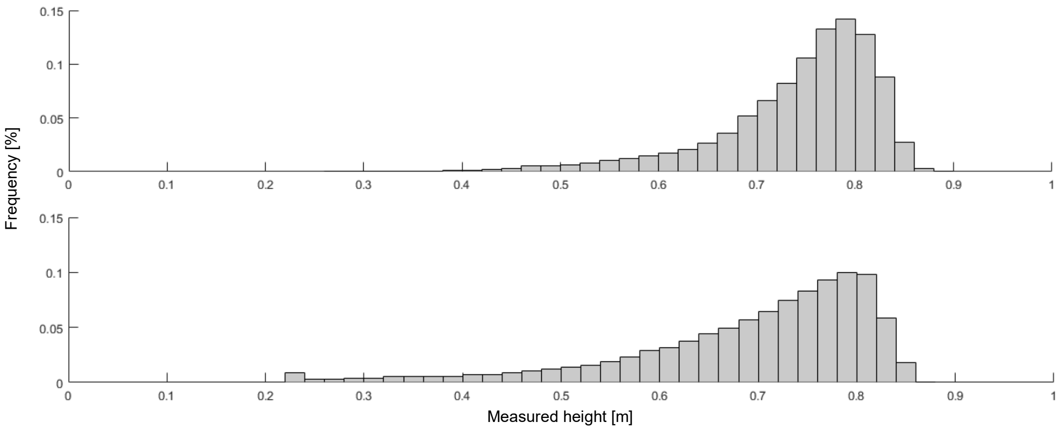

Fig. 5: Normalized histogram of measured field height in real model (top) and 3D-surface model (bottom) of crop plants with a real and simulated laser scanner

Fig. 6: LiDAR-sensor-based edge detection with 3D-surface model of crop plants

A scenario for LiDAR crop edge detection and steering control was built in simulation (fig. 5 & 6). It uses the same algorithm and control architecture as the CLAAS Laser Pilot. Machine dynamics can be simulated by multi-bodies in Gazebo or by a single-track model in MATLAB/ Simulink. Based on the environmental and sensor model concepts challenging cases such as broken edges, tight turning curves or low crop density can be investigated.

4. Conclusion

A concept of a simulation framework for environmental sensors with multilevel abstraction in agricultural scenarios was proposed and successfully implemented. An example of the LiDAR-based steering control by crop edge detection demonstrates the potential of the environment for optimizing and creating new processes, in particular control systems algorithms and sensor integration. Used in an early stage of development it can support recognizing implementation errors. By systematic and reproducible function tests of software components optimization of algorithms is possible prior to field tests and may reduce the complexity of real experiments. Future work will focus on further simulation function levels.

5. Acknowledgements

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