SELF-DEVELOPED SMALL ROBOT FOR TOMATO PLANTS DETECTION #9413

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ABSTRACT

A mobile (robot) measuring station for tomato plant detection has been developed, equipped with different sensors and a self-developed hardware and software background. The development aims are the applications in precision crop production: artificial intelligence-based detection, imaging, data collection, automation, and remote sensing. The robot is fault-free in field conditions and is therefore a key development tool for precision farming and digital agriculture. The measurement system developed is modular. It consists of three main components: the power supply, the data processing and storage unit, and the physical quantity measuring units (sensors).

INTRODUCTION

Recently, several studies have drawn attention to the need for a paradigm shift again, the current adverse effects of agriculture on the biosphere cannot be reduced with the knowledge provided by research based on traditional experiments (1). Global food security is threatened by several sources, such as population growth, meat consumption trends, and the effects of climate change (2). In addition, increasing pest, disease and weed tolerance is putting increasing pressure on both conventional and precision technologies (3). To alleviate the burden of these challenges, it provides the opportunity to automate and robotize certain aspects of the farming process.

The definition of a robot

A robot is any entity that perceives, interprets, and intervenes in a dynamically changing environment in an adaptive manner. Another important feature is the communication and the collaboration. An autonomous system needs information to make the right decisions before acting. If the autonomous system has incorrect information, it will make incorrect decisions and perform incorrect actions.

Agricultural robots

The type of agricultural robots is the following: data collectors, weed killers, plant protectors, harvesters, and appropriate combinations of these, as well as robots in animal husbandry (milking, feeding, monitoring robots for the health of herds). The mechanical operation of agricultural robot systems requires real-time correction. The GPS coordinates must be determined from point to point as soon as possible with high accuracy (5). The so-called real-time differential correction (RTK) can greatly increase the accuracy of GPS data (6). In the last decade, RTK technology has undergone great development (+/-1 inch).

Small smart robots

The "Internet of Things" (IoT) technology has spread in agriculture as well, thus providing a “big data” for the data source and intervention of precision methods (7,8). As IoT technology has evolved, intelligent agricultural robots need both flexibility and adaptability to move and act in field environments (9). Robots must work with these technologies and above-mentioned conditions. Their design must adapt not only according to predetermined parameters, but also adapt to changes in environmental factors. Nowadays, many options are available that facilitate the processing of information from large databases. Artificial neural networks have been incorporated into agriculture in many applications because of their advantages over traditional systems. The main advantage of neural networks is their ability to make predictions based on information. Neural networks can be designed instead of actual programming. In the case of robots used in agriculture, not only is the changing environment a big challenge, but also the fact that the equipment often must handle living, vulnerable materials. Applied artificial intelligence also integrates the opportunities offered by machine learning.

MATERIAL AND METHOD

Robot structure, concept

When planning and choosing the methods used, we tried to take advantage of the opportunities provided by the methodical planning used in engineering sciences. In addition (10), we also used a now widespread method, the "From Toy to Tool" process. The equipment has a compact, modular structure, both hardware and software. Hardware contains three parts: the power supply, the control system, and the intervention devices (Fig. 1).

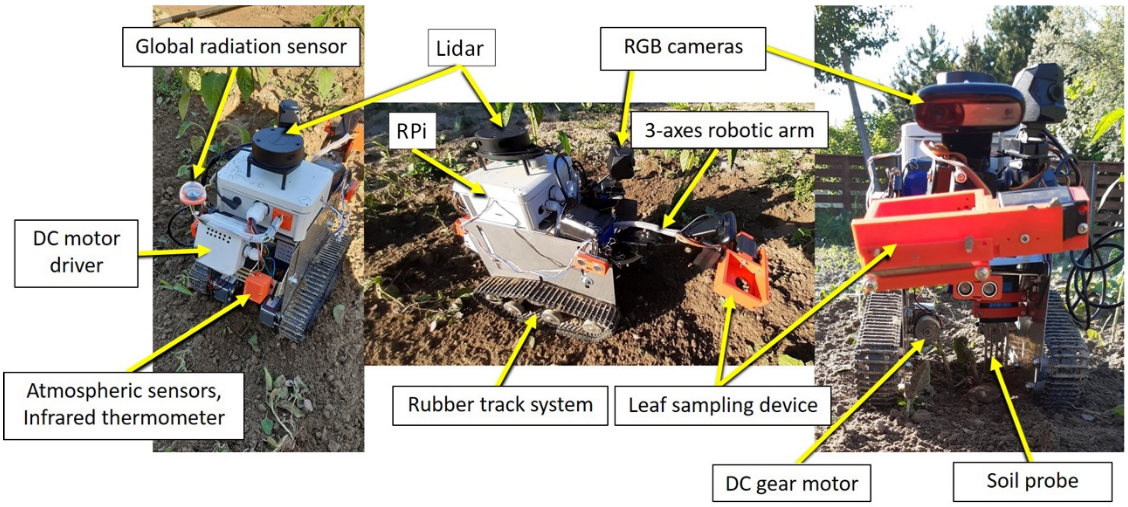

Fig. 1. Build by the robot (Source: own figure).

The robot is based on a metal frame structure. The height barrier of the robot can be easily adjusted to the specific plant culture, which helps with the positioning of the sensors and sampling equipment. The running gear is a rubber belt for proper traction on the ground, and due to this design, the control of the robot can also be easily realized. The robot is powered by two direct current gear motors (DC). The speed of these motors can be regulated, and thanks to their high torque, they are suitable for moving the robot. The maximum speed of the equipment is 20 cm/s, which is sufficient for data collection and detection. An H-bridge motor control circuit is responsible for the operation of the motors, which can directly control the two motors simultaneously. Its power supply is ensured by a LiPo battery pack via a control unit, a battery management system (BMS). The batteries have a 3S3P design and produce a direct voltage of approximately 12V, which supplies energy directly to the drive and, on the other hand, to the other lower voltage systems with the help of voltage regulation electronics (DC-DC converter). Approximately 4 hours of operating time are available under operating conditions. The central unit of the device is a Raspberry Pi 4 microcomputer, which is complemented by a "Shield" panel specially developed for this robot, on which the other additional electronic components and connectors are located. Half of this "Shield" is for easy fitting of other electronic components to the central unit. It is also equipped with an RGB camera that can be positioned along two axes with servo motors. For orientation, the equipment has three ultrasonic distance sensors as well as Lidar and GPS, so it can move autonomously between the rows of cultivated plants. It also collects information from the environment, e.g.: global radiation, air temperature, humidity; and soil properties: soil surface infrared thermometer, temperature, moisture content, EC, pH, and NPK. The soil properties sensing probe is driven into the ground by a stepper motor through a gear-rack transmission, and with the help of an H-bridge motor control circuit. The robot is equipped with a three-axis servo motor-based arm, at the end of this arm there is a leaf sampling device. This structural element can be modeled like a pair of scissors, the positioning of which is performed manually by the robot operator. The robot was programmed in the Python programming language to control the mobile unit. Full control and optimization of the machine is available to the user. Both wired (LAN) and wireless (Wifi, Bluetooth) connections are available on the robot platform. The robot is controlled by a specially designed application via a PC, smartphone, or tablet.

RESULTS AND DISCUSSION

Artificial vision is used to identify syndromes of plant diseases, pests, and pathogens by considering several visual characteristics that fall into three general categories: biological (morphology), spectral reflectance characteristics, and visual structure. The robot can automatically collect information from the environment at predetermined intervals, including global radiation, humidity, temperature, atmospheric pressure, soil moisture and temperature, and soil properties (EC, pH, NPK). With the help of these data, it is possible to archive an information base for crop production systems. It means an agricultural monitoring system to support the predictions. By analyzing images from the RGB camera, artificial intelligence based on neural networks can recognize changes in plant parts and inform the robot operator. This method used a neural network model created through the Edges Impulse platform. With this artificial intelligence-based model, the robot can detect part of unhealthy leaves. This makes it possible to take samples for expert (machine or human) determination of the cause of the actual change (nutrient deficiency, infection, etc.).

Using another model based on a neural network, the robot can detect ripe tomatoes and store photos. Using these images, with the distance between the tomato berries and the camera (measured by Lidar) can be used to estimate the tomato yield, using the OpenCV post-analysis method. During the process, the mass of the tomato berries is extracted from the completed images through post-processing. A color-segmented mask was used by transforming the images with the appropriate algorithm to determine the surface of the ripe berries. Based on the calculated surface and Lidar distance data, the volume of the berries can be determined by 3D modeling (Fig. 2). The mass of ripe tomato berries can be calculated by introducing the average density characteristic of tomato varieties.

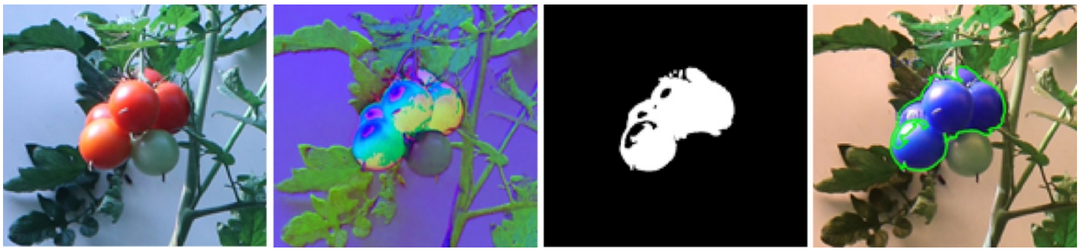

Fig. 2. Steps of image processing for tomato yield estimation (Source: own drawing).

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