Challenges of Autonomous In-field Fruit Harvesting and Concept of a Robotic Solution

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Abstract: Since the beginning of humans cultivating plants in fields, agriculture underwent a continuous shift from purely manual labor over simple machinery to more and more automated processes. Autonomous driving with navigation and self localization in the field is state of the art. Also, automated machines for fruit processing are available as well. In cases where the fruit is damageable and varies in size and shape, automated processing is challenging. One example of such damageable fruits are strawberries. Size, weight, and shape at the optimal ripeness can vary a lot. Additionally, a change from ripe to overripe occurs relatively quick and is sometimes hard to recognize. A further challenge when harvesting strawberries is a dense leafage that can cover the fruits partly or completely. In this paper, a concept of an autonomous in-field strawberry harvesting robot for non-elevated but ground-raised strawberry plants, with or without a tunnel, is presented. The robot is supposed to use multi-spectral imaging and machine learning based ripeness classification. Besides the overall concept, first data of this early-stage project is shown, too.

1 INTRODUCTION

The overall goal of the project presented in this work is to develop a small scale robotic system for automated harvesting of strawberries. A small scale robot can easily scale up to any farm size by being deployed multiple times in parallel, while a lower investment per unit makes the system also attractive for smaller farms. The SHIVAA (Strawberry Harvester: an Innovative Vehicle for Agricultural Applications) robot will be deployed in open fields alongside human workers. Initially, we will focus on the picking itself, however numerous additional use cases have already been identified and will be elaborated further during the running project.

1.1 Motivation

Since the beginning of agriculture, mankind sought for ways to improve the efficiency by increasing the area of land manageable by one person. Starting with animal-pulled machinery, over fuel driven multi-purpose tractors to currently partially self-driving connected tractors, the complexity and automation in agriculture increased by time. Generally speaking, a higher degree of automation in agriculture can lead to higher efficiency and an improved supply safety. A combine harvester is a huge machine that allows a single operator to harvest hundreds of tons of wheat per day, the current top rate is around 800 t in 8 h. Yet, there are still fruits and vegetables that are more labor intensive. Strawberries are a high priced fruit that up to date needs human labor for harvesting. Experienced human workers can harvest up to 40 kg per hour, while the mean value over all workers is more around 20 kg per hour. With increasing salaries in countries where workers are classically recruited or travel restrictions as seen during the COVID-19 pandemic crisis, finding human workers for the harvest gets more and more complicated. Here, a robotic harvester can fill the gaps from missing human work force.

1.2 Challenges

Many challenges exist for full automation of agricultural processes in general. Focusing on sensitive fruit such as strawberries puts further challenges in terms of careful handling while picking and deploying the fruit. Furthermore, aiming for a robotic harvesting in standard outdoor fields without special adaptations to the harvester leads to more problems that need to be

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solved. Figure 1 shows a standard strawberry field covered with tunnels (with eight ridges each tunnel). The left photo shows the field in autumn. Strawberry plants can have leaves effectively hiding the fruit-to-be-harvested from sensors on a robot. Here, mechanisms to exhibit the fruits to a sensor need to be developed. In Figure 1 (right) the field in spring is shown. Some fruits are not visible in the camera image, others are partially covered. All the challenges need to be tackled while guaranteeing a speedy operation. Clearly, a robot with a worse picking quota than human workers will stand no chance of being widely adopted by the market.

1.3 Related Work

Robotic systems which are capable of harvesting strawberries autonomously have already been presented by multiple research groups. Some presented robots were designed for elevated-trough cultures where the strawberry plants are grown in a trough elevated at between 50 cm to 100 cm above ground. Feng et al. describe a mobile robot platform with a 6-DOF manipulator and sonar-based navigation (Feng et al., 2012).

Ge et al. use a similar environment of elevated-trough cultures and describe very detailed the image based fruit detection and localization (Ge et al., 2019). Xiong et al. designed and evaluated different strawberry harvesting robots. While some tests of a previous version were carried out in tunnels and on sandy ground, they focus on elevated-trough ("table-top") cultures in the later publication (Xiong et al., 2020). However, they show interesting results and insights, e.g., regarding the gripper, regarding picking in clusters of strawberries, and regarding varying lighting conditions.

Hayashi et al. present an evaluation of their system in a field-test. The environment is an evaluated-trough setting, too. Interesting is their comparison of machine and human assessment of the strawberries' maturity and their solution concept focusing at night operation and allowing task-sharing with human workers (Hayashi et al., 2010).

To achieve a similar picking speed as a human picker, it may be necessary to use dual arm manipulation. (Le Flecher et al., 2019) described a visual predictive control strategy for two arms sharing a common work space. An interesting agricultural robot, which combines several approaches to navigate autonomously in a field was proposed in (Post et al., 2017), even if it is not explicitly about strawberry harvesting. A number of robots have already been published that are able to navigate in the open field and perform manipulation tasks autonomously, e.g. the robots Artemis (Schwender et al., 2014) and Coyote (Sonsalla et al., 2015). However, these systems are not specialized enough for rapid crop manipulation and consequently too slow for use in the strawberry field.

Most of the papers listed deal with the cultivation of strawberries on elevated-trough cultures or cover only partial aspects of the overall process necessary for strawberry harvesting. However, the target environment of the robot concept described in this work is non-elevated, ground-based and dam-raised strawberry plants, outdoors, with or without tunnels.

Currently, there are several pre-product solutions of robots for harvesting strawberries. One example is the Agrobot[1], which makes use of up to 24 arms working in parallel. It is stated, that the robot is suitable for table cultures as well as free field strawberries. The company Harvest Croo Robotics provides a comparable system[2], with 16 arms working in parallel. The system can scan a fruit in a 360° view to assess the ripeness. A visual system is used to locate the fruit prior to picking it from the plant. Systems for table cultures are the Rubion[3] developed by the company Octinion and the Dogtooth[4] robot with two picking arms.

Finally, work focusing on multi-spectral or hyperspectral image classification has been published, too. Multi-spectral image based classification is used in several applications. UV, visual, and SWIR 2D images are used by Tiedemann et al. for the classification of a large range of different materials in coarse-waste recycling (Tiedemann et al., 2021). For applications in agriculture Pasolli et al. give a good overview of studies and methods. There, airborne and satellite data collection in the spectral range of 400 nm to 2,500 nm dominate but terrestrial collections and the methods (which are good candidates for the strawberry classification) are discussed, too (Pasolli et al., 2018). Devassy and George compare different regression models for the estimation of the firmness of strawberries using hyperspectral imaging (Devassy and George, 2021).

Klaoudatos et al. present a non-mobile system consisting of a standard 6-DOF manipulator, a fin ray gripper, and a vision system that was tested in laboratory only. However, the vision system gives interesting insights by an implementation that uses classical image processing on red and green channels only plus depth information from a Kinect sensor (Klaoudatos

[1] https://www.agrobot.com/e-series; as of 2022-04

[2] https://www.harvestcroorobotics.com/; as of 2022-04

[3] https://picking.technology/; as of 2022-04

[4] https://dogtooth.tech/; as of 2022-04

Figure 1: Left: Photo of an outdoor strawberry field with an 8-row tunnel, taken in autumn (Tiedemann, 2022b, under CC-BY 4.0). Right: Lower view position between the ridges, taken in spring (Tiedemann, 2022a, under CC-BY 4.0).

et al., 2019).

Although many of the pre-product solutions provide promising approaches, two major drawbacks stand out in our opinion. Solutions that already work in the field are mostly very large and complex machines that, although performance still needs to be improved, require a large investment volume. Smaller systems, with lower barriers to investment, have so far been limited to specific types of cultivation such as table crops and their performance is far too slow for widespread use, yet. And a general solution for standard non-elevated/non-table-top fields is still missing.

2 PROPOSED ROBOTIC CONCEPT/SOLUTION

2.1 Requirements

A detailed list of all the requirements we found in workshops and discussions with farm owners is beyond the scope of this paper. However, the most important requirements are summarized as follows

- operation in open field, all weather conditions possible: rain, heat, frost, mud, dust,... an IP rating of IP65 shall be reached.
- row width is different on different farms. Current setpoint is 1 m row width, needs to be easily adaptable
- experienced human pickers can pick 40 kg of strawberries per hour, the mean is around 20 kg. Given the mean weight of a strawberry, the rover shall reach around 25 harvested strawberries per minute.
- a payload capacity of 90 kg for the final system shall be reached. 90 kg of ripe fruits are to be expected per row in high season.

2.2 Overall Concept

2.2.1 General Platform Concept

The general robotic concept forsees a four wheeled rover system, roughly the size of a table. Four legs will be used to reach a platform height well above the strawberry plants. Two manipulation arms with specific gripper elements are mounted to the robot such that they can operate below the main platform. All four wheels will be actively driven, while only the two hind wheels are steerable in order to reduce the number of actively actuated joins as far as possible. A detailed description of the current system design is provided in Section 2.3.

2.2.2 Concept of Operation

For start of operations, the robot is deployed by a human at the strawberry field. Once enabled, the human operator navigates the robot to the first row to be harvested using a remote control unit. After manual placement, the robot is standing with its body over the first strawberry plants. By enabling the harvesting mode, the robot starts its operational loop:

1. detect strawberries
2. extract gripping poses for
   (a) ripe strawberries
   (b) foul/overripe fruits
3. harvest all strawberries below robot using linear drivable manipulation arms
4. put ripe fruit into selling boxes / overripe fruit into waste bin

5. if end of row is not reached move platform forward one body length begin at 1., else
6. execute row change and start at 1.

2.2.3 Scenarios

The overall objective of the project is to enable the SHIVAA system to move mostly autonomously in the strawberry field and harvest strawberries. The robot should be deployed in an outdoor field, possibly with humans working in close vicinity of the robot.

The system includes a base platform which can move around the field on wheels. The current concept forsees 4 driven wheels, two of which are also steerable, see also Section 2.3. The base platform is equipped with one or more manipulators, each of which can in turn hold a gripper as an end-effector. For detecting ripe strawberries, the platform and/or the manipulators are equipped with suitable imaging sensor technology. Additional sensor technology on the platform enables self-localization in the field and reliable tracking of the strawberry rows. The platform is also equipped with a receptacle for empty strawberry crates, which are ready loaded with hulls.

The demonstration scenario intended for SHIVAA follows the concept of operations as described in Section 2.2.2. After manual deployment at the first row, the rover autonomy is initiated and the robot starts picking strawberries. The rover drives forward a full body length and initiates a detection cycle. The poses of the ripe fruits to be harvested and the foul fruits to be sorted out are extracted and sent as two individual lists to the manipulation planner. After planning the manipulator trajectory, harvesting of a fruit is conducted, before a new manipulation plan is issued. Once all fruit are harvested or sorted out beneath the current robot position, the rover drives forward a body length and the cycle starts over again.

Further scenarios investigated are (i) leave picking: The leaves of the plants are to be reduced before the harvesting season. This might help the plants to build better fruits, reduce humidity and hence fungal attack and consequently the use of fungicide. (ii) Mowing between the rows: On farms where there is grass in between the rows of strawberries, the robot can be used to keep the grass short. (iii) keeping track of ripeness: while driving through the rows (during harvest or other tasks) the robot can take the ripeness of the fruits to project an expected harvest for the next time frame. A forecast of the harvested amount of the next week can help setting efforts and prices.

2.3 Robotic Platform

The SHIVAA system is intended to be a small, cost-effective system for harvesting strawberries on dam cultures in the open field (see Figure 2). The unloaded weight of the system is limited to max. 120 kg, so that it can be carried by four persons if necessary. To allow autonomous operation of the system for at least 3 hours, the robot is equipped with a 1.5 kWh Li-Ion battery.

The robot can move forward on four actively driven wheels with a top speed of min. 6 km/h and a preliminary estimated nominal torque of each drive of 35 Nm. To allow various steering modes the rear wheels are equipped with individually controllable steering actuators. Because of the layout of the dam crops the track width is fixed to exactly one meter with a wheelbase of approximately two meters. To compensate ground unevenness up to at least 100 mm by the undercarriage the rear legs are coupled via a differential.

Strawberry picking is performed on both sides and below the robot, so that the lower face of the central body must be at least 0.8 m above ground level to ensure a wide enough manipulation area.

Two manipulator arms, each equipped with a gripper, are used for picking and manipulating fruit. Since a manipulation space of at least one meter along the strawberry row is to be covered on both sides of the dam in order to be able to statistically compensate for non-uniform growth, the manipulators can be moved on linear guides along the sides of the robot.

The further kinematic chain of each manipulator consists of three DOF arranged in a plane orthogonal to the longitudinal axis of the robot, and an additional rotation around the central axis of the end effector. The reach of one manipulator is approximately 0.8 m, with the length of the upper and lower arm segments being 0.4 m each. The manipulator arms follow a low inertia design principle to allow fast movements with high accelerations between picking and placement locations. To achieve this, all four drives are shifted to the base of the robot so that their mass does not need to be accelerated except along the linear guide. The drives are kinematically coupled to the arm base. The torque is transmitted to the respective joints via belt drives, with the more distant joints being coupled from joint to joint. Because the axis of rotation of the fourth DOF is not in the same plane as the other joint axes, the third and fourth DOF are coupled differentially. The movement of these two DOF is therefore dependent on the interaction of the same two drives. A plastic bevel gear is used for the differential coupling. Figure 3 shows a schematic view of the arm

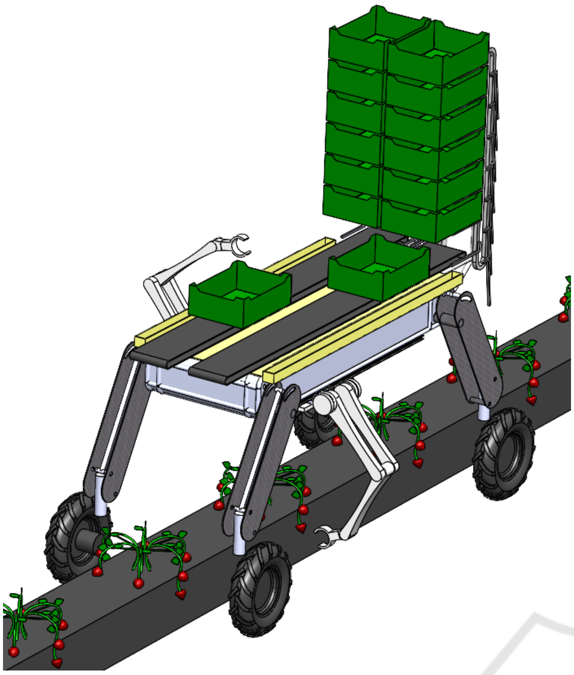

Figure 2: Mechanical concept of the proposed strawberry picking robot.

actuation concept.

The actuation of the arm DOF is done by BLDC direct drives. External rotor motors are used for this purpose. The transmission to the respective joint axis is performed by up to two belt gear stages with a total reduction ratio of up to 1:6. The transmission ratio is selected according to the respective nominal torque requirements, whereby the same motor is used for each degree of freedom.

The picking process takes place independently on both sides of the robot, with the fruit being picked below the robot and placed directly into provided boxes above the robot. Each fruit thus only needs to be touched once, minimizing the risk of damage to the fruit. Due to the limited linear travel speed of the manipulators along the longitudinal axis of the robot, the deposit boxes are moved along on conveyor belts to follow the manipulator position. Full boxes can be transported to the back of the robot while empty boxes are supplied from a storage system on the robot. Fruits that have been classified as overripe or bad fruits during image recognition are not placed in the boxes but in depositories along the robots flanks.

In order to keep the inertia of the entire manipulator as low as possible, especially the end effector should apply minimal weight. In this case the end effector will probably be a gripper with a maximum of two DOF, whereby the fruit is first sucked in and held in the center of the gripper by a vacuum system so that, in a second step, the fruit can be easily enclosed by the gripper. Separating the fruits from the plant occurs by a combined pulling and twisting motion with the help of the manipulator arm. The required under pressure system can be placed in the central robot body, so that only a pneumatic tube and the electric wiring has to be transferred through the arm.

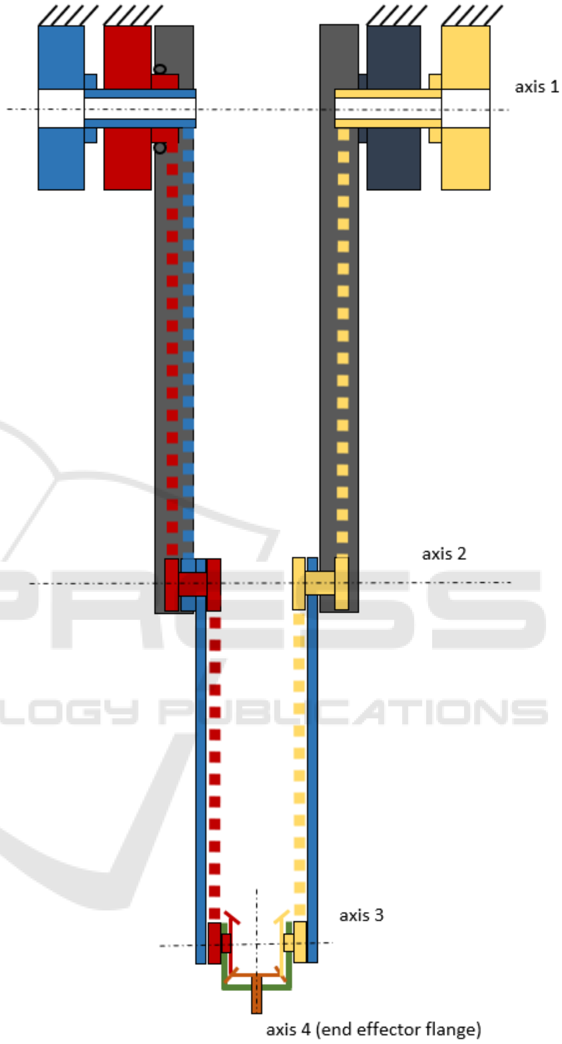

Figure 3: Schematic representation of the arm actuation, where the black motor actuates axis 1, the blue motor actuates axis 2, and the red and green motor are coupled differentially to axes 3 and 4. If they rotate in the same direction, the end effector rotates around axis 3. If they rotate in the contrary direction, the end effector rotates around axis 4.

2.4 Sensor Setup for Fruit Detection and First Data

The tasks the sensory system of the robot has to fulfill are (1) the detection of strawberries within the robot's workspace, (2) the classification of the strawberries in ripe, not yet ripe, and overripe, and (3) the localization of the ripe and the foul strawberries (both have to be harvested and will be put into different boxes). Optionally, a detection of leaves could be a task for the robot in case leaves have to be removed or pushed aside by the robot. And finally, one additional demand might be that the system needs to be run either at night (compare (Hayashi et al., 2010)) with controlled but fully artificial lighting or at day time – with brighter environmental lighting but varying with dawn, dusk, and weather conditions.

For the solution of several classification tasks in agriculture and other applications a combination of visual images (sometimes with a separate "red-edge" channel) and near-infrared (NIR) images are used – sometimes extended by UV and/or short-wave infrared (SWIR) images (Tiedemann et al., 2021). In a first phase, sample data of ripe, not ripe, damaged and overripe strawberries is collected in 17 spectra from 250 nm to 1,550 nm. Based on the first data collection a subset of the 17 spectra is selected for the final prototype and is evaluated in a second phase. The up to 17 2D-images are used together for the detection and classification task. If a strawberry is detected and needs to be harvested, its position relative to the robot is determined using a further sensor. For this task a time-of-flight (TOF-) camera, a stereo camera, or a lidar will be used. The selection of the sensor to be used in this task is done based on tests in the first project phase.

The multi-spectral imaging (MSI) data sets are collected with three different cameras (UV camera, visual camera, SWIR camera) and with different spectral filters. Figure 4 shows an exemplary overview of one MSI data set.

To analyze and to visualize the relation between single spectral components and the classification of ripeness, false color images can be used. In Figure 5 an example is depicted with the spectral images of 845 nm, 1,450 nm, and with an image taken by the SWIR camera with no filter as components red, green, and blue, respectively. At the bottom right strawberry a defective/foul area can be recognized quite easily.

The actual advantages of MSI can be utilized fully when all available spectral images (dimensions) are used. However, this data is hard to study and to understand for humans. E.g., the false color image uses only 3 of the 17 dimensions. However, to classify ripe from non-ripe from overripe strawberries and from other parts of the plants, machine learning (ML) based methods will be applied and studied. These methods use all 17 dimensions and are supposed to be able to classify correctly between the classes mentioned above. First tests will be carried out with support vector machines (SVM) which were dominating classification tasks until deep methods as the convolutional neural networks (CNN) showed better performance in several applications. However, these were high-dimensional classification task like image classification with hundreds or thousands dimensions and with local relations between input dimensions. It is expected that such properties need not to be used in the classification task in this project, thus, no object classification / no classification of a whole strawberry. Rather, a classification on single pixel basis is planned as a first step, using only the 17 gray values of the different spectra. In a second step pixel classifications can be grouped by size and class leading to an ordered list of strawberries of different classes and sizes.

To get a first impression of the task the classifier has to solve, again a visualization with only up to four dimensions is helpful. Besides more elaborated and complex methods as principle component analysis (PCA) or t-SNE visualization, a simple projection from the 17-dimensional to a three-dimensional space can give interesting insights. Figure 6 shows a projection on the dimensions 324 nm, 740 nm, and 1,550 nm with the color as fourth dimension encoding the class of the pixel as labeled ground truth. There, the background (blue) can be separated clearly from the rest, stem and leaves (yellow and green) are harder to separate (but could be possible), the brown non-ripe area and the black (defective part) area are close to the red (healthy and ripe) area but seems to be separable.

These first results of the data analysis give a good reason to start with simple classification methods as SVM or a simple multi-layer perceptron (MLP). Furthermore, clustering, followed by a feature selection and dimensionality reduction study will be next steps.

As a preparation for the next following step, a first data collection in the field has been carried out. Figure 7 shows the camera setup placed between the ridges (dams). Four cameras have been used there to collect multi-spectral data: (1) a UV camera, (2) a SWIR camera, (3) a visual camera without an internal IR filter, and (4) a standard visual camera with IR filter. The first three cameras were consecutively equipped with different filter configurations to take separate images per spectral band. The fourth camera was used to take a visual reference image.

Next steps in this early project state are the preprocessing of the collected data, a manual analysis of the data and running first classification tests.

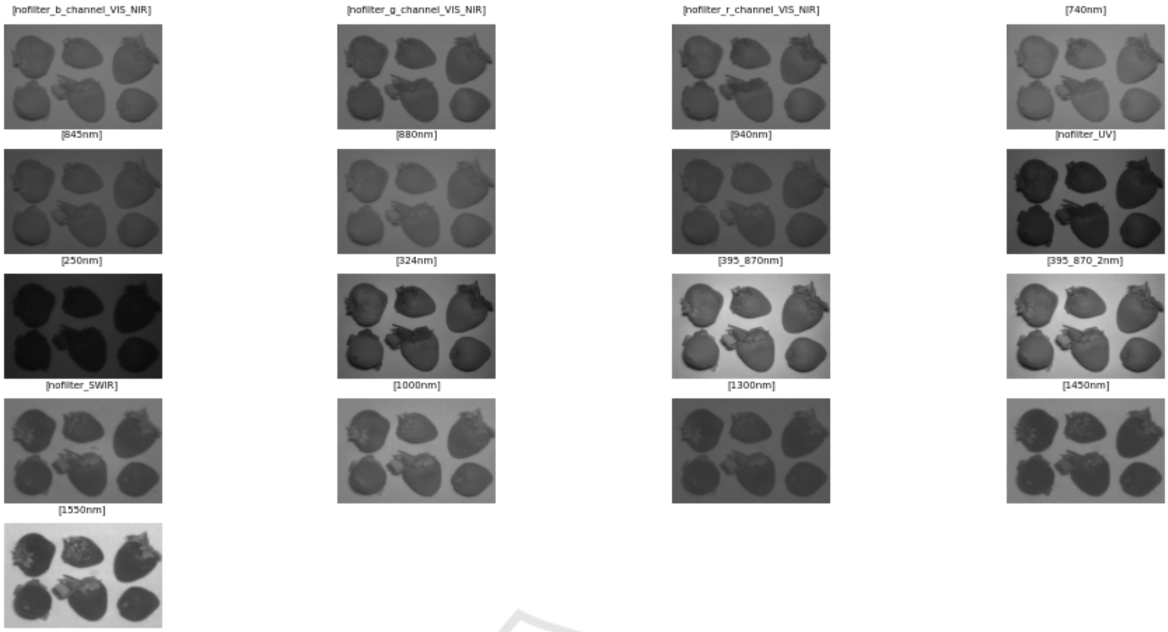

Figure 4: Overview of all images taken of a single scene. The images were taken with one of three cameras (UV, SWIR, visual) and with one of multiple filters (or with no filter) in the range of 250 nm to 1,550 nm. The set of all images is used as a single multi-spectral imaging (MSI) data set.

Figure 5: Example of a false color image.

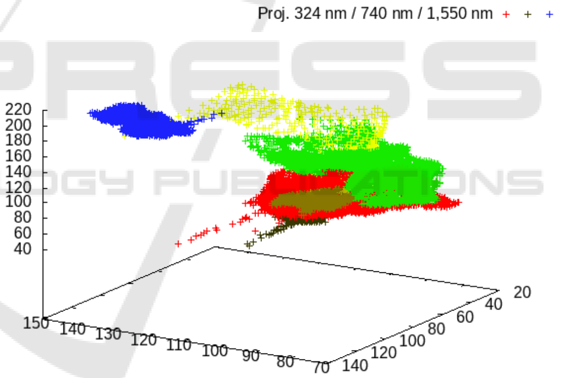

Figure 6: Projection on three axes of a sample data set. Blue is background, green are leaves, red is the strawberry fruit in a healthy state, yellow is the stem. Especially interesting are (1) the brown area within the red area which is a non-ripe strawberry and the small black part below the red area which is taken from a defective part.

3 SUMMARY AND OUTLOOK

This work presents a concept for an in-field ground-based dam-raised strawberry harvesting robot, its mechanical setup, its sensor equipment, and planned classification methods. Furthermore, first collected data is shown and very first results of a data analysis are discussed.

The next steps cover (1) the system specification, (2) the mechanical design process in different steps and (3) further in-field data collections. A set of potentially applicable machine learning classification methods will be evaluated using the data collection sets.

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Figure 7: Setup used for a first in-field data collection. A rigid frame carries four cameras used to collect the multi spectral data. In this setting the frame is placed between the ridges.

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