For5G: Systematic approach for creating digital twins of cherry orchards

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Abstract: We present a systematic approach for creating digital twins of cherry trees in orchards as part of the project "For5G: Digital Twin". We aim to develop a basic concept for 5G applications in orchards using a mobile campus network. Digital twins monitor the status of individual trees in every aspect and are a crucial step for the digitalization of processes in horticulture. Our framework incorporates a transformation of photometric data to a 3D reconstruction, which is subsequently segmented and modeled using learning-based approaches. Collecting objective phenotypic features from individual trees over time and storing them in a knowledge graph offers a convenient foundation for gaining new insights. Our approach shows promising results at this point for creating a detailed digital twin of a cherry tree and ultimately the entire orchard.

Keywords: 5G, cherry tree, deep learning, digital horticulture, digital twin, knowledge graph, orchard, phenotyping, photogrammetry, precision farming, UAV

1 Introduction

Smart farming and precision agriculture rely on accurate data as a foundation for decisions to counteract current problems such as climate change and to meet the ever-growing food needs of the world's population. Using digital twins in agriculture can help growth optimization, early pest detection, yield forecasting and conserve resources in cultivation. The digital twin can inform the farmer about crop conditions or anomalies and thus assist in decision-making processes or provide information to agricultural robots. Ultimately, the goal is to relieve the farmer of having to be on-site and allow them to assess the condition of their crops solely through the digital twin.

In recent years, the creation of digital twins in agriculture has become an increasingly important topic in research [PN22]. The main task is to capture and model the complexity

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of a living entity and its dynamic reaction to the environment [PCA21]. Several approaches exist in related work acquiring digital twins, from plant modeling to real-time monitoring with feedback mechanisms [PN22].

In this paper, as part of the project "For5G: Digital Twin", we present a concept for creating a digital twin using an unmanned aerial vehicle (UAV) with a 5G network for cloud access. Figure 1 shows an overview of the approach. The core idea is to acquire photometric data of a cherry tree using the UAV. The obtained 2D image data is sent through the 5G network to a cloud server for real-time analysis. 3D point clouds are generated using the images and subsequently segmented into separate plant organs such as leaves, trunks, branches, etc. Each organ instance is then separately modeled using a geometric model, resulting in a set of parameters describing the phenotypic traits. Combining the data of all tree organs into a knowledge graph provides a snapshot of the tree in time. Repeating the scans makes it possible to track the trees' development over time, intra- and inter-seasonal. Making this data accessible to the farmer can be a valuable aid in his decision-making process.

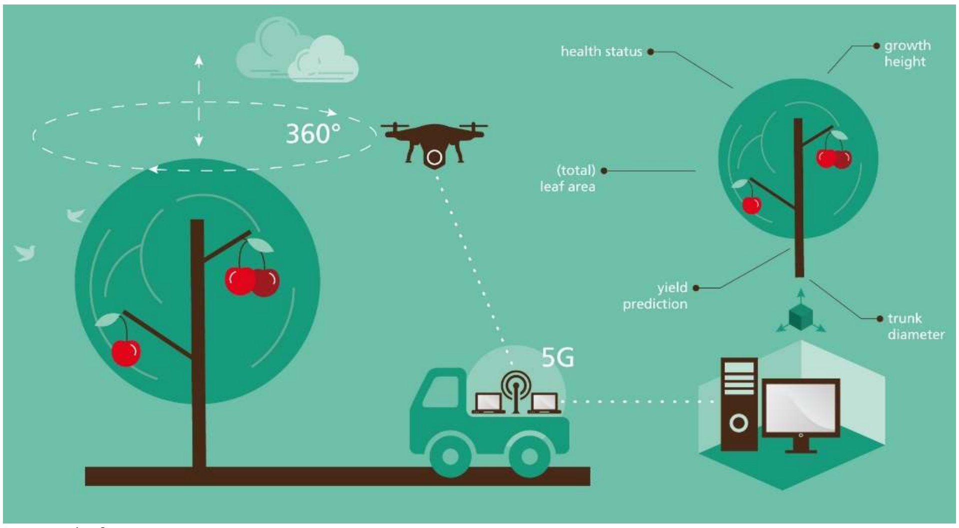

Fig. 1: Workflow of the presented pipeline. The mobile 5G campus network enables the system to operate at different locations

2 Methodology

For the development and testing of our setup, we cooperate with a local cherry orchard research facility, the Obstinformationszentrum Fränkische Schweiz (OIZ). The project is divided into five sub-projects, which will be presented in detail in the following sections.

2.1 Data acquisition and campus network

We use a DJI M300 UAV equipped with a photogrammetric camera to record high-resolution videos. The UAV autonomously flies around the cherry trees on a pre-programmed flight path covering as many views as possible. Through this approach, our solution is very flexible regarding application environments, as data can be acquired very efficiently and independently of the local topography. Since a 5G network is not yet available everywhere, a mobile campus network is used to provide high-speed connectivity between UAV and server. The server provides the resources to evaluate the data immediately after acquisition without needing locally available public data networks.

2.2 3D reconstruction

We use state-of-the-art open-source software to reconstruct the cherry trees from the recorded image stream. The reconstruction is based on Structure from Motion (SfM) [SF16] and Multi-View Stereo (MVS) [Sc16] algorithms. SfM attempts to capture the scene's structure using a moving sensor. It determines camera and scene geometries by matching image features across corresponding images. The camera geometry contains information about the camera's poses and the scene geometry is composed of triangulated points representing the scene as a sparse map. With the retrieved geometry, MVS searches for stereo correspondences in the image stream and computes the depth map for every image individually. Afterwards, the depth images are fused to obtain a dense point cloud. Since monocular reconstructions suffer from scale factor ambiguity, calibration targets are placed in the scene to obtain metrically scaled reconstructions. A result of a cherry tree in vegetation dormancy is depicted in Figure 2 on the left.

2.3 Segmentation

The generated point clouds form the basis for further analysis. In order to do meaningful feature extraction, a semantic understanding of the data (e.g. differentiation between different tree organs and background noise) is required. Our goal is to develop an automated solution for this semantic segmentation based on an artificial neural network (ANN). Manually annotated data is used to train an ANN to map each individual point of the 3D tree reconstruction to a corresponding target class, e.g. cherry, stem, leaf, etc. Prior experiments revealed that relying on network architectures that interpret the data points in the form of graph representations [Wa19] outperforms approaches based on raw point clouds like PointNet++ [Qi17]. To train and infer this learning-based model on large point clouds, we experiment with different data preprocessing steps like subsampling [SGS23] to develop a streamlined pipeline for efficient semantic segmentation of trees. The segmentation results in a separate point cloud for each instance of each organ (e.g. each individual cherry).

2.4 Model and feature extraction

The following processing step automatically extracts relevant and interpretable features from each segmented point cloud. To ensure robust feature extraction, we use a model-based approach incorporating prior knowledge of a cherry tree’s morphology. For each tree organ with a corresponding segmentation class, we have developed/will develop a specific geometric model that represents relevant features as numeric parameters. Therefore, the feature extraction step is actually an optimization problem fitting a model to the segmented point cloud by varying the model's parameters.

The cherry tree’s leaves are modeled using an existing leaf model adapted to cherry tree leaves. Currently, geometric models for trunks and cherries are being developed. The trunk is modeled using a sequence of cylinders with different radii. The cherries are currently modeled as simple spheres. Other plant organs like blossoms and buds will be considered in the future.

2.5 Knowledge graph

Finally, a cherry tree-specific knowledge graph is constructed to store collected data and phenotypic characteristics. Observing the graph over time can assess a cherry tree's current state and temporal development.

The knowledge graph is based on a Prov-Ontology [PR22], which organizes the results of the feature analysis in a straightforward graph structure. We have developed an appropriate ontology based on the characteristics of a cherry tree. It contains types like tree, branch, trunk diameter, cherry size, etc. Thus, using a semantic query language such as SPARQL, the knowledge graph can be queried to obtain specific information about the tree’s features and provides the basis for assessing each tree’s performance over time.

3 Results

As interim results, we present the workflow and our pipeline exemplary for one characteristic tree organ – the trunk. Based on already acquired images, multiple cherry trees have been reconstructed as 3D point clouds and annotated, as displayed in Figure 2 on the left. In a subsequent step, an ANN was trained on subsampled parts of these point clouds with the goal of creating a model to perform semantic segmentation, exemplarily shown in Figure 2, by differentiating trunk data points, highlighted in orange, from non-trunk data points.

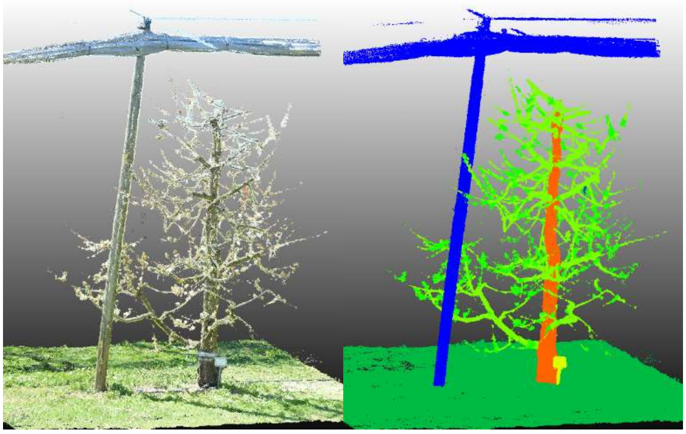

Fig. 2: Exemplary picture of a 3D cherry tree reconstruction with original colorization (left) and hand-labeled visualization with colored target classes (right). Orange indicates the class tree trunk.

Once a sufficient fraction of the trunk data points has been segmented, they are fitted into the geometric trunk model based on meshes (see Fig. 3). The metric point cloud reconstructions allow us to precisely measure core features like the trunk diameter at arbitrary heights with high precision. In the first tests, the deviation between the measured diameter of the real trunk and our modeled trunk was below 6 mm. We expect the segmentation results to further improve once more training data is available.

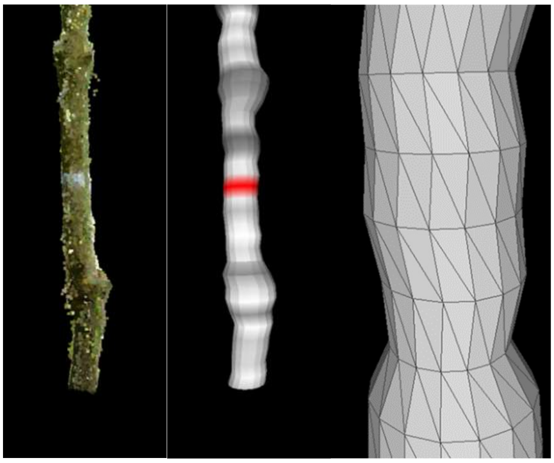

Fig. 3: The segmented point cloud of the trunk (left) and the trunk model was automatically fitted to the data in the feature extraction step (middle). The red mark indicates the detected position where manual measurements of the trunk diameter are taken for validation. At the right, a close-up view of the stem model is shown to illustrate the geometry of cylindrical pieces with different radii.

4 Conclusion and future work

The proposed framework for digital twins of cherry trees opens a wide range of opportunities in research as well as in the operation of orchards. At pomiculture research stations, digital twins could help replace labor-intensive manual assessments of individual trees like counting buds, flowers and fruits with a highly automated data acquisition and evaluation process. Thereby, this technology not only reduces labor expenses but also facilitates an accurate and objective means of monitoring tree conditions. For example, the effect of the environment on the plant can be assessed more accurately. Researchers and farmers could benefit from digital cherry tree twins as collecting objective features over time enables precise monitoring of the seasonal development of trees and thus potentially improves yield predictions and the optimal harvest time estimation. Furthermore, the data can support the farmer in recognizing critical conditions of individual trees, such as drought stress, nutrient deficiency or pest infestation, allowing him to take countermeasures early. This could lead to a more efficient and more sustainable operation of orchards.

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