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Cloud Based Architecture for Automated Weed Control

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***Abstract*—Automated weed control has received an increased interest from the scientific community in recent years. Even tough there is fairly large number of available approaches and even commercially available systems for weed control, several challenges exist that need to be assessed. Most of the approaches use automated detection of weed and apply herbicides with sprayers on the most infested regions of the land. Automated weed control has proven to reduce the quantity of applied herbicides, thus reducing the pollution of products, land and water. Being a part of the precision agriculture paradigm, automated weed control can be performed only by accessing large amount of on the field sensory data including images and videos from unmanned areal and ground vehicles. With the increased granularity of the regions which is a consequence of the increased resolutions of the used vision sensors, there is even larger need of fast and reliable data processing architectures that allow large volumes of data to be instantly processed. Furthermore, the weed detection includes computer vision algorithms that have high time and space complexity and that often depend on parameters that need to be tuned. By gathering and processing data from multiple fields, the parameter estimation can be performed with higher accuracy and greater reliability. In this paper we propose a cloud based architecture that elevates the automated weed control by using the possibilities introduced from the cloud to gather additional aggregated knowledge from the process of automated weed control and further improve the process of weed control data processing and parameter estimation. We discuss the main benefits of the proposed architecture and the challenges that need to be overcome for it to be introduced to the agricultural communities.**

I. Introduction

Precision agriculture is improving the management of the land by viewing it not as a single entity, but as multiple parts that need separate attention. Based on the definition by [1]: "Precision agriculture is the management of an agricultural crop at a spatial scale smaller than the individual field". Based on this definition, by separating the individual field to multiple parts, the complexity of the management domain is significantly increased. Each separate part is being analyzed and treated as a single entity and with the improvement of the sensing technologies [2], these separate entities are becoming smaller and smaller. With the increased volume of the gathered data, the need for improved and faster architectures for gathering and processing is imminent. The complexity of the precision agriculture data processing is even bigger if we include the separate parts of the analysis that need to be performed, sometimes with very fast processing speed, in order to obtain the necessary information and to be able to react on time based on the obtained knowledge.

Automated weed detection, as part of the precision agriculture paradigm, is a complex task that requires multidisciplinary approaches in order to be resolved. Automated weed detection is consisted of analysis of separate land patches or individual plants and estimation of the weed infestation on the land patch or individual plant species identification. Both of the tasks are quite complex when taken into account the differing attributes of the plants in different stages of their development and under different light conditions. The usage of cloud based services for precision agriculture has already been introduced. A labor monitoring and data processing cloud based approach is described in [3]. Authors use the approach to monitor the labor productivity trough labor monitoring devices. In [4], a framework for cloud-based Decision Support and Automation systems for precision agriculture in orchards is proposed. The framework allows processing data of different formats and control of field devices. In [5] authors discuss the challenges that need to be overcome to use cloud based services for decision support in precision agriculture. A method for remote sensing observation sharing based on cloud computing (ROSCC) is proposed in [6]. Authors experimented with the system for large soil moisture mapping. In [7], the author gives an interesting discussion after interviewing several farmers and people that work with big data incorporation in farming. The author warns about the challenges that the technological advancements introduce to the simple farmers and that the research should be driven towards the effects desired by the users.

Automated weed control is a part of the precision agriculture paradigm that deals with the removal of unwanted plants from the fields. The precise weed management or weed control has plenty of benefits and according to [8] they are both economic and ecological. The economic benefit is consisted of the removal of plants that compete with the wanted plant in the same soil, and the ecological benefit is evident because the precise automated weed control is shown to reduce the usage of herbicides significantly. One such example that reports significant herbicide reduction is presented in [9], where authors use Unmanned Air Vehicles (UAVs) to support patch herbicide spraying in maize crops. The usage of UAVs for precision agriculture is already present, especially in the process of weed infestation detection in field patches and will improve the food production in future. The potential of UAVs is well described in the literature [10].

However, little has been researched, about the potential of using cloud based services to address the big data challenges that arise from the very nature of the weed control process. Weed control is consisted of detection and elimination of unwanted weeds. The process of detection and elimination is already being automated [11]. However several challenges exist that need to be addressed.

In this paper we discuss the existing challenges for application of automated weed control in the fields and propose a general cloud based architecture that could overcome these challenges. The paper is organized as follows: In section II we discuss the main motivation behind the work presented in this paper. Then in section III, we present the main architectural design of a cloud based system for automated weed control. Finally in section IV we discuss the main advantages and disadvantages of the proposed architecture.

II. Motivation

As previously discussed, the automated weed control could be beneficial to the agricultural food producers by reducing the unwanted weeds and increasing the yield per land unit. However, several challenges still exist that need to be overcome:

- Robust models for weed detection
- Reliable and safe methods for weed removal
- Adoption of the new technologies by farmers

The weeds are plants, and as any other plant, they grow. During their growth, weeds differ in size, shape and color. Furthermore, different kinds of weeds are present in the field at the same time, which makes their detection a greater challenge. The ultimate goal for maximum herbicide reduction and maximum yield from the fields, while keeping the pollution at minimum, is to be able to single out each weed plant and identify its species. By achieving this, any system for automated weed detection and removal would be able to treat separate weed plants with different herbicides or perform a mechanical removal of the weeds. The challenge here is to have a machine learning based model for detection of the different types of weed, using fusion from different types of sensors. One of the most popular sensors for this task are cameras that can be mounted on UAVs. According to [12], multispectral cameras can be used for generating weed infestation maps. These maps use processing intensive algorithms for generating image stitching and the complexity is increased by adding other kinds of sensors as additional information from the fields.

Another challenge is the safe removal of the weed from the fields. The weed removal can be performed both by spraying herbicides [13] and using mechanical tools [14]. The usage of mechanical tools requires much greater precision in order to limit the damage to the useful plants. Such precise control requires intensive data processing and planning in order to be executed. Furthermore, while the spraying tools require the sensing systems not to underestimate the weed infestation in the patches that need to be sprayed, the sensing units for the mechanical tools must not overestimate or falsely identify crops as weeds.

The final, and maybe the most important, challenge is the farmers' adoption of new technologies. Since most of the available proprietary solutions for precision agriculture limit the farmers to certain types of tools from certain producers, we believe that a general software architecture and implementation could aid the new technology adoption not only for the big agricultural producers, but also from the small and medium sized farms. To meet the discussed challenges, the proposed architecture must have the following qualities:

- Deal with large volumes of data from variable types of sources
- Control variable types of hardware actuators
- Be able to make decisions and give suggestions for different environments and under variable conditions.
- Be able to process fast
- Be affordable

The only way to have all of these qualities is to use a cloud based solution where the farmers will be able to collaboratively achieve the same goals. First, by using the local data for local decision making and for building local models for the weeds (the flora on a local scale in a small community varies less than when observed globally). Secondly, by using the cloud processing for on-demand decision making, which is much cheaper for individual farmers that cannot afford expensive hardware for data processing.

III. System architecture

In this section we present a general architecture that is able to address the requirements discussed previously. The general architecture is shown in Fig 1.

One of the main challenges for a successful weed control application is the data acquisition. As previously discussed, the UAVs can be used for such purpose. Furthermore, ground based cheap sensors can aid data gathering from the fields. Such sensors have already been presented as a viable and cheap alternative for inter-row weed detection [15]. The data obtained from any source including the data that has been input by the farmers can be used by the cloud based services for multiple purposes. Initially, before enough data is gathered from the fields, the data processed by the users will be used for model generation. Machine learning approaches have already been applied for the process of weed detection. The best results are obtained, however, by using deep learning approaches [16], such as deep convectional networks. As reported, these approaches have high accuracy in successfully segmenting the weed parts from the images. When combined with previously processed data from other sensors, highly reliable models can be generated for weed/crop discrimination. In fact, this is the main goal of any automated weed control system, prior to the treatment of weed. The high complexity of the deep learning approaches can be overcome by using on-demand GPU cloud services that are already provided by different cloud service providers, such as Amazon Web Services [17] and Google Cloud Platform [18]. The feature selection from the other types of sensors can be combined by using machine learning approaches and deep learning architectures. Most

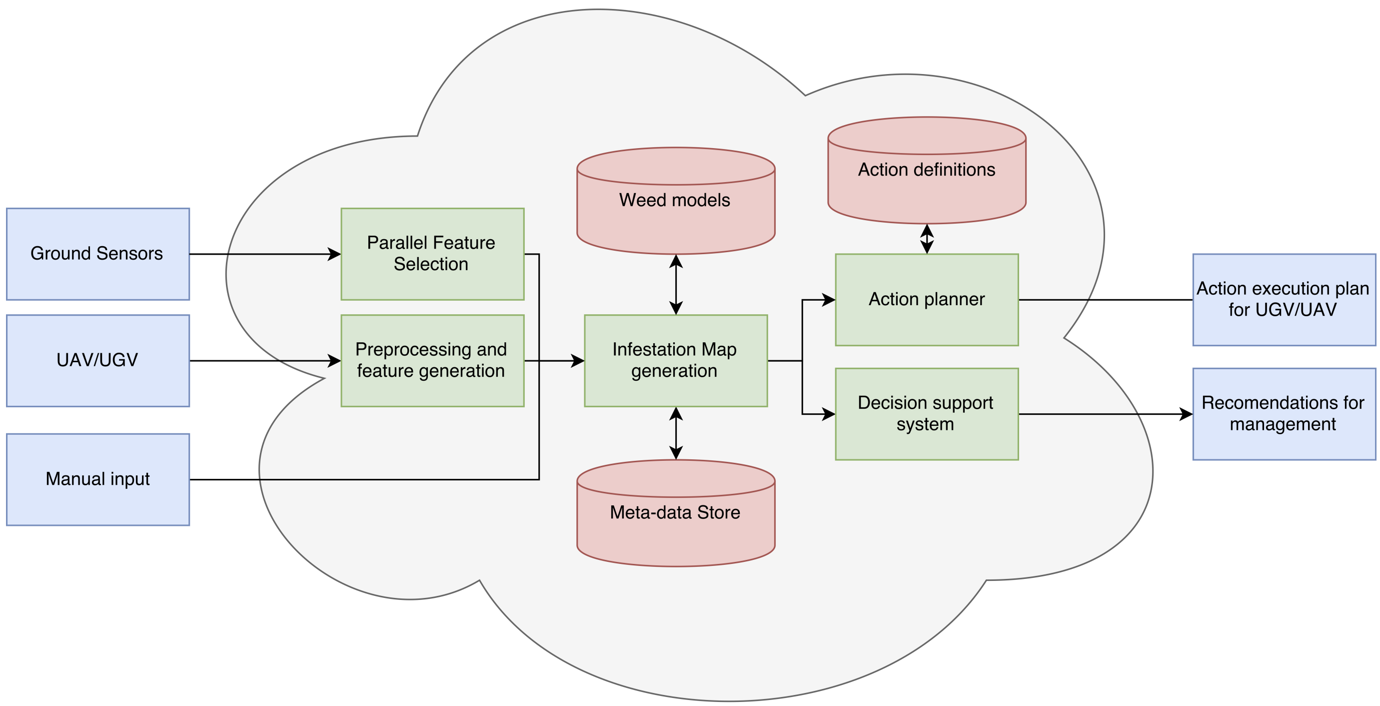

Fig. 1. General system architecture

of the leading cloud service providers also provide machine learning modules that can be used for both model generation and weed detection. Deep learning approaches can be used after enough data has been gathered from the fields. Initially the models can be obtained by using manual feature generation and more traditional machine learning approaches.

Most of the machine learning approaches, however, require certain parameter tuning that is dependant on the data. Since the farmers in certain geographical proximity deal with similar challenges, meta-data can be stored about the specific models that need to be used by specific farmers in a close geographical location. This meta data can be obtained by both data analysis and farmer input. As it can be observed in the general architecture, both are taken into consideration. The trained model can be used for generating an infestation map. The geo-location combined with the sensory input and the imagery can be used together to form the infestation map. The images are combined and stitched together using the geo-location and a 2D or 3D map can be formed from the observed land. There are already several commercially available products that allow this kind of map building from images. The weed infestation can be easily marked on the obtained map based on the prior processing.

The obtained infestation map can than be employed in the process of planning. The geo-location data is already available and the locations of the weeds or the infestation of the land patches have already been determined. Therefore, a plan for spraying or weed picking can easily be devised by using existing planning approaches. This planned strategy can then be used by the farmers or by Unmanned Ground Vehicles (UGVs) or Robots to automatically treat the weed infestation. The main benefit of moving the planning to the cloud is that the planning, which often demands a large computing power, doesn't need to be executed very frequently. Thus, the small or medium farmer is not required to actually own an expensive computing hardware and additionally makes the tools that can be used for weed removal more versatile.

A plug and play approach is recommended when dealing with different kinds of sensors and actuators. Since different actuators can perform different actions, all of the available actions must be pre-configured and known to the cloud based system. The advantage is that once one of the users inputs this data, it can be used by any other user that uses the cloud based weed control system. The usage of cloud based services for planning for automated machines has already been introduced in the literature [19].

In Fig. 4 a more detailed flow of the infestation map generation is presented. Based on both the user input and the sensory input, the Image Processing part segments the different parts of the images and generates features for combining the images in a map. After the weed is detected using the model, the user can observe and provide input in order to improve the models. There are also approaches where the model is generated in a self-supervised manner [20].

The weed detection model that is stored in the cloud and the meta-data associated with it are constantly updated and improved. In this way, different models can be used in different seasons, and for different locations. One must note that although the proposed approach is useful for farmers in general, it is not a fully automated approach because the farmer interaction with the system is necessary until the weed detection models achieve acceptable performance. A simple user interface is necessary to allow the farmer to tune the system and give their input. An interactive approach for initial segmentation such as [21] can be used to allow an expert or the farmer to segment the weeds from the crops in the image set to generate an initial dataset, based on which the models can be initially built. In Fig.3 the initial learning module user input is depicted in higher detail. As it can be observed, it requires input from the user. However, this is performed in a simple and elegant way so that the user does not necessarily need to be precise in the selection and with time, after system obtains enough data from multiple users, it will not be required at all. In Fig.2 a mockup of a simple interface for the farmer to input the initial data based on the acquired images from UAVs or UGVs is presented. This kind of segmentation has already been used in some of the more popular graphics editors such as Gimp [22]. Any touch enabled device could be used to obtain the input from the farmers.

IV. Discussion

The proposed architecture describes a self improving cloud based service for weed control. The data acquisition for the system can easily be performed by the farmers by using the crowd sourcing approach and can be used to build reliable weed detection models. The proposed architecture can be applied for both controlling an autonomous vehicle for weed removal, or for decision support for farmers that don't own autonomous vehicles, but would like to treat the weed infestation themselves. This architecture is suitable for both large and small farms.

The main challenge while implementing such system would be the ease of use and the motivation for technological advancement from the farmers. The proposed semi-automated approach requires an intuitive interface for the farmers. Since the input sensors for weed infestation estimation and weed plant detection are vision based, the initial segmentation can be fairly easy performed. For small amounts of data the traditional machine learning approaches are more suitable, and for large amounts of data, deep learning approaches can be employed to obtain even better results.

As discussed by [7], farmers do not like to be pushed by new technologies. Rather they are more interested in being able to influence on the technologies themselves, and apply them as they see fit. This architecture takes this into account and, at least initially, requires the attention of the farmers and provides them the ability to tune and control, without being able to impact the system reliability. Furthermore, since the system is based as a service, it will be easy to adapt to any data input.

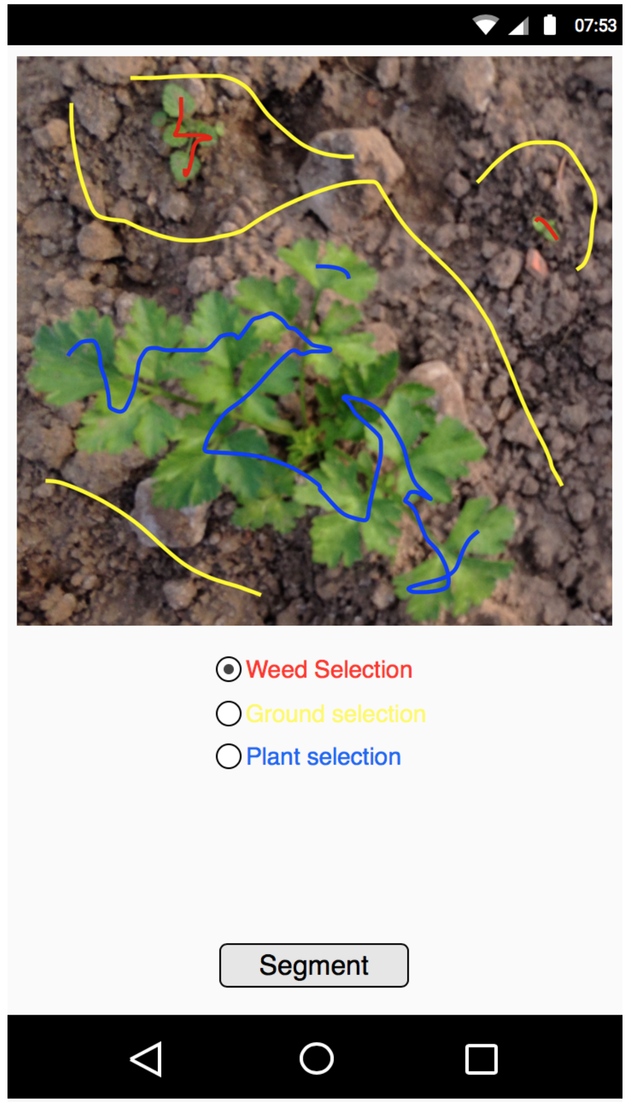

Fig. 2. Semi-automated data input interface

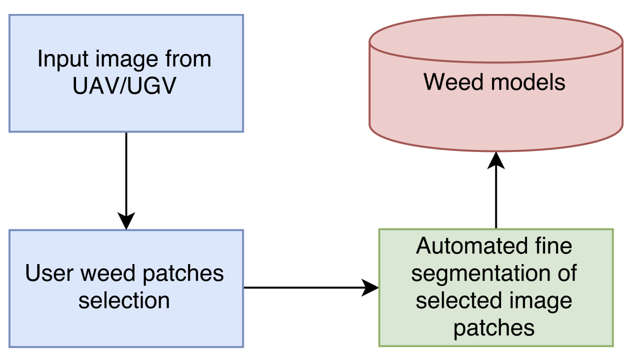

Fig. 3. Semi-automated data input flow

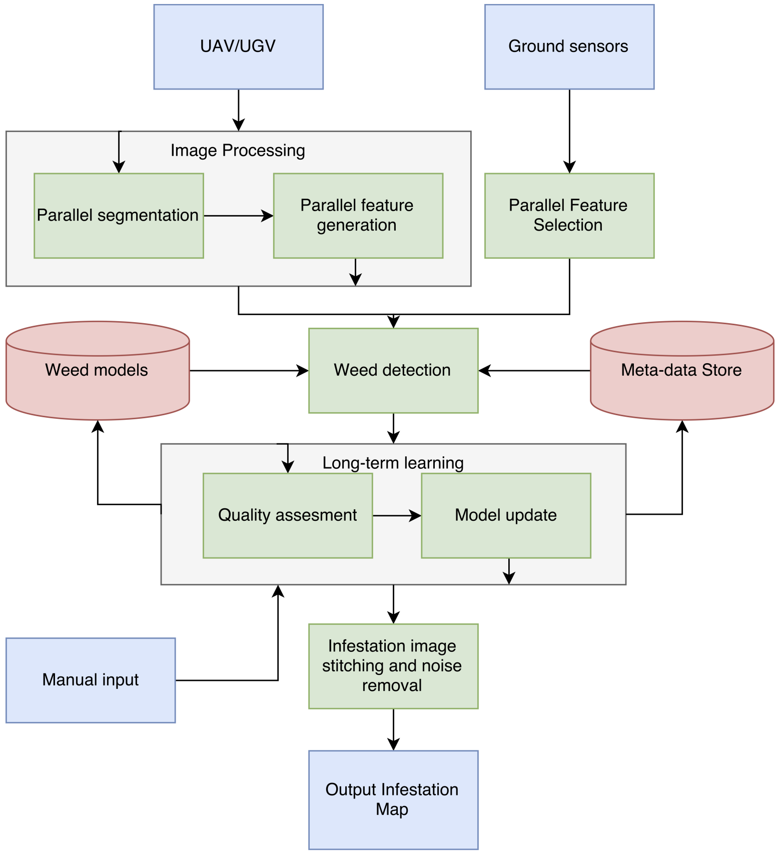

Fig. 4. Infestation map generation

The main drawback of this architecture is that it requires the user interaction and it also requires a large user base in order to achieve optimal performance. Be that as it may, the architecture allows the user to tune the parameters and even to obtain a temporary optimal model that would allow weed detection and treatment for specific weed types on localized land units.

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