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Published in:
8th IFAC Symposium on Intelligent Autonomous Vehicles, 2013

DOI (link to publication from Publisher):
[10.3182/20130626-3-AU-2035.00055](https://doi.org/10.3182/20130626-3-AU-2035.00055)

Publication date:
2013

Document Version
Early version, also known as pre-print

[Link to publication from Aalborg University](#)

Citation for published version (APA):
Hansen, K. D., Garcia Ruiz, F. J., Kazmi, W., Bisgaard, M., la Cour-Harbo, A., Rasmussen, J., & Andersen, H. J. (2013). An Autonomous Robotic System for Mapping Weeds in Fields. In *8th IFAC Symposium on Intelligent Autonomous Vehicles, 2013* (Vol. 8, pp. 217-224). Elsevier. <https://doi.org/10.3182/20130626-3-AU-2035.00055>

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An Autonomous Robotic System for Mapping Weeds in Fields

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Abstract: The ASETA project develops theory and methods for robotic agricultural systems. In ASETA, unmanned aircraft and unmanned ground vehicles are used to automate the task of identifying and removing weeds in sugar beet fields. The framework for a working automatic robotic weeding system is presented along with the implemented computer vision systems.

Keywords: Agriculture, Automation, Autonomous mobile robots, Computer vision, Co-operation, Trajectory planning

1. INTRODUCTION

The use of pesticides is detrimental to the environment. However, farmers must treat their fields against weed infestations to keep their business profitable. The current practice is to spray the entire field even if the weed distribution is heterogeneous. This herbicide discharge can be greatly reduced if the application is targeted only at actual infestations instead. However, it is required that the infestations are discovered and identified before they begin to compete with the crops. Practically, this is not possible if the weeds have to be surveyed by humans; this is simply too costly.

The ASETA project (la Cour-Harbo (2010)) is developing a system for autonomously mapping weeds in fields by means of robots, airborne and ground-based, fitted with advanced camera equipment. The airborne robots are based on small-scale helicopters that provide the system with multi-spectral aerial images. Using data from the helicopters, the system identifies infestations in a field and then dispatches autonomous ground vehicles to the infestations to exactly identify and localize the weeds.

In this paper, the framework and key technologies for integrating this system are described.

1.1 Previous Work

In their review of the current state of the art of robotic weed control systems, Slaughter et al. (2008) report more than 50% yield loss if weeds are not controlled in row crops. They further note the problem that the weeds closest to the crops are the most harmful and that these are also

the most difficult weeds to control. The consequence is that some fields must be hand-hoed, which is costly and inefficient.

The topic of site-specific weed control is surveyed by Christensen et al. (2009), where they classify the treatment of the fields in four levels:

- (1) Individual plant treatment
- (2) Treatment of grids (several plants)
- (3) Subfield treatment
- (4) Whole-field treatment

The ASETA project works in the first two levels, focusing on single plants and smaller patches.

1.2 The ASETA Case

ASETA is working with a system of ground based and aerial vehicles. Both are unmanned and autonomous. Through a series of steps, the robots will identify and localize any weed infestations in a given field. The ASETA case works with thistle (*Cirsium arvense*) infestations in sugar beet fields (Kazmi et al. (2011)).

A theoretical infrastructure of an agricultural decision support system for robotic site-specific weed management was proposed by Fernández-Quintanilla et al. (2011). That work takes a holistic approach and encompass everything needed to make such a system operational. In their terminology, the ASETA project focus on the subsystem called the “current year decision system”. This is concerned with the current state of a field and which treatment to apply to maximize the immediate yield.

* This work is supported by the Danish Council for Strategic Research under grant no. 09-067027 (ASETA). See www.aseta.dk for more details.

2. METHODS

2.1 Multiscale Imaging

The core idea in ASETA is to use a multiscale imaging approach. This entails taking aerial images at high altitudes, and then gradually lowering the altitude, to obtain images with higher resolution. At some point the ground vehicles will take over and perform imaging of individual plants.

A simplified process with a single unmanned aircraft system (UAS) and a single unmanned ground vehicle (UGV) looks like this:

- An operator defines the bounding polygon of a field.
- The UAS takes images of the field from high altitudes.
- The images are processed, indicating areas of interest for closer inspection.
- The UAS flies to the indicated areas and obtains higher resolution images (lower altitude), which are processed for indications of weed infestations.
- The UGV is dispatched to the areas that need attention.
- The UGV identifies the exact shape and position of each piece of weed and reports it to the system.
- The process continues until all weeds in the field have been mapped.

This multiscale imaging approach saves time because it quickly directs the UGVs to actual infestations. It also has the advantage of acquiring overview images of the entire field in the process. These images can be used for weed estimates, in the locations, where the UGVs do not go. However, aerial images are not as precise as ground-based images. Christensen et al. (2009) deems aerial based sensing fitting for the two coarsest classifications of site-specific treatment (sub-field and whole-field). They, however, did not have UASs in mind, but rather piloted aircraft and satellites; UAS imaging provides even higher resolutions. By using ground-based sensing to correct and calibrate the aerial measurements, the aerial images may be used at the next levels (several plants and single-plant).

2.2 System Architecture

The conceptual structure of a system with one UGV and one UAS is shown in Fig. 1. It consists of a task manager that automatically decomposes the task of the entire system (i.e. to survey a given field) into tasks for the individual subsystems. The supervisors interpret the tasks and command the vehicles to move to the indicated positions, while they keep track of the execution. The data from the vehicles are processed to update the map of the field in the database. When such updates occur, the task manager factors the new information into the plans and changes the tasks of the vehicles accordingly.

The description of the simplified process above (Sec. 2.1) is static, in the sense that information only travels from the UAS to the UGV. The system proposed here follows the same general idea but is more dynamic because it allows the vehicles to work in parallel and cooperate.

A short description of the components is given below.

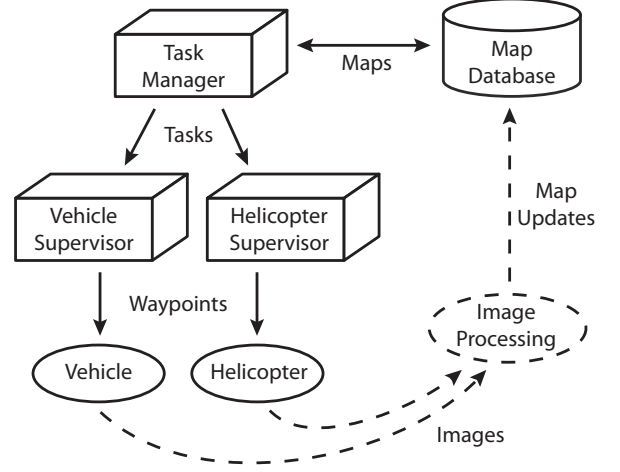


Fig. 1. The conceptual system of ASETA. The task manager creates tasks for the vehicles. The tasks are handled by the supervisors, which monitor and provide the vehicles with waypoints in the correct sequence. The data obtained by the vehicles are processed to provide updates to the maps in the database.

Task Manager The job of the task manager is to decompose the overall task in such a way that the UGVs and the UASs perform the execution in the fastest and least resource demanding fashion.

In essence, what the task manager has to do is solve a job shop scheduling problem. Because the abilities of different vehicles are overlapping. E.g. the UAS can quickly photograph the entire field, albeit at a low resolution. This is also possible for the UGV; it will take a long time, but provide a high resolution. So the job is to figure out which vehicles to use to acquire which images.

Further, the images must be taken at different locations, so the execution time of a task is not only dependent on the time it takes to take the photograph, but also the travel time between the locations. This alludes to a case of the traveling salesman problem.

So, the task manager is tasked with two cases of combinatorial optimization. The approach of the ASETA project is to solve these using genetic algorithms (see section 2.3).

Supervisors The supervisor interprets the tasks given by the task manager and provides the vehicles with lower-level commands such as waypoints, reference trajectories or when to take an image. The primary task of the supervisors is to ensure that the tasks that are passed on to the vehicles are executable, but they also function as a standardized interface between the task manager and the vehicle. This way, the task manager can ignore the dynamics of the vehicles when planning.

Vehicle and Helicopter In the ASETA case, the UAS is based on a small-scale helicopter (Fig. 2) and the UGV is based on a four wheeled robotic platform (Fig. 3). But, the general system allows for several, possibly different vehicles. In this way, the system can be suitable for a range of different scenarios.



Fig. 2. The UAS, based on a Maxi Joker 3 RC-helicopter, equipped with a multi spectral camera mounted in a gimbal device (front), a mini-ITX computer (underside), and IMU and GPS (on tail).

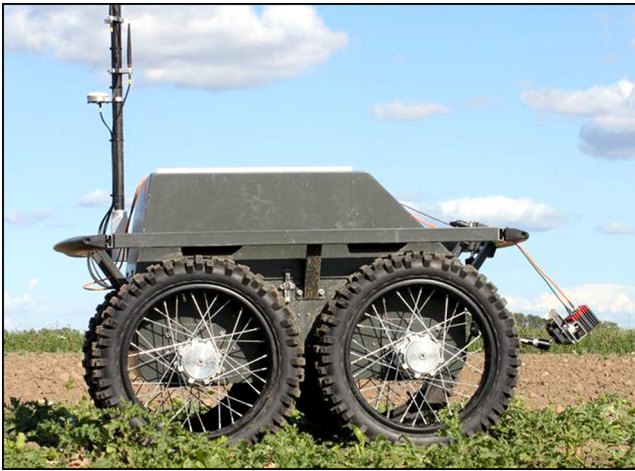


Fig. 3. The UGV is based on a the RobuROC4 platform from Robusoft. It is a skid-steered, four-wheel driven vehicle with custom onboard computer, sensor suite, and camera setup.

Image Processing The automatic processing of the image data provided by the vehicles is essential to the system. The ASETA project does work in both ground-based and aerial imaging. The aerial image processing focus on determining weed patches and the ground-based image processing works with the identification of single plants. These two topics are described in sections 2.4 and 2.5.

Map Database The end product of the entire automation exercise is to build a map of the field, indicating spots of weeds. Initially, the database will hold only the outline of the field, and as the vehicles provide more information, the maps will be populated.

The ASETA project focus on mapping thistles in sugar beet fields, but having several other image processing algorithms and sensors on the vehicles could enable the system to produce several different maps in the same run. These maps could include soil nutrition levels, plant growth stages, pest infestations as well as the weed map.

2.3 Automatic Planning

The goal of the system is to have a complete survey of a given field. The automatic planner decomposes this goal

into several states, each composed of a location and an action that the vehicle must take in that location. The vehicles must visit these locations in a sequence. So in order to save fuel and time, the planner must find the shortest path between the coordinates; this is a case of the traveling salesman's problem.

The planning is done with a genetic algorithm (GA). The GA used for the planing is based on the path-representation described in (Larrañaga et al. (1999)), and uses the four mutations: Displacement, exchange, inversion, and insertion (Fogel (1993); Banzhaf (1990); Michalewicz (1999)). This GA does not guarantee to find the optimal solution nor to converge to it, however it will often converge on good candidate solutions. The difference between the candidate and the optimal solutions is tolerated, because the environment and vehicle dynamics incur so much uncertainty that it is unknown whether the optimal solution in terms of distance is in fact the best.

Although the GA might not converge to the optimal solution, it must be given some computation time to arrive at whatever near-optimal solution it is converging to. It is usually up to the designer of the algorithm to decide on how much time the algorithm is given, which is not always easy at design time as the runtime increases with problem size and is dependent on the quality of the initial guess. A contribution from the ASETA project is an adaptive stopping criterion for GAs, that indicates when the algorithm has reached an acceptably good solution (Hansen and la Cour-Harbo (2013)).

The distance that the robots travel depends on the plan that the GA constructs. A simple measure of the solution quality is the euclidean distance between the points. This is easily computable but introduces sharp turns that are not realizable by the vehicles because of kinematic and dynamic constraints.

Currently, an alternative to the Euclidean distance measure is being studied under the ASETA project. It bases the distance measure on Dubins curves, which are composed of line and arc segments. These curves are differentiable and match the vehicle dynamics better, but they also introduce more computations as well as a continuous variable in the heading of each waypoint. These two problems are addressed by using the Euclidean measure first, and later in the process when the solutions are converging substitute the distance measures with Dubins measures for the relevant arcs (i.e. the candidate arcs for the final solution). This work is based on the alternating algorithm of Savla et al. (2005) with the considerations of headings introduced by Ny et al. (2012). The notations and results of Shkel and Lumelsky (2001) are used to achieve efficient computations of the Dubins curves.

2.4 Aerial Image Processing

The aerial image processing is based on color analysis. The fact that different plant species show different colors is used to discriminate between them. Physiological internal processes determine the important features for discrimination (i.e. chlorophyll absorption bands, red edge inflection point) and can be detected by narrow band multispectral imaging with a sufficient spatial resolution. Hence, it is

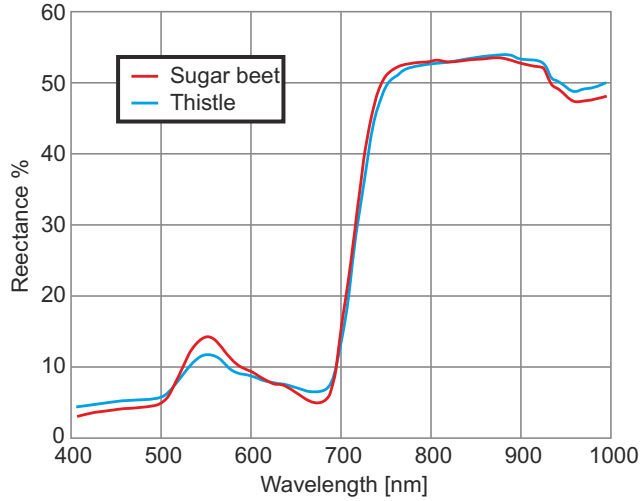


Fig. 4. Spectral signature of sugar beet (red) and *Cirsium Arvense* L./thistle (blue) in the visual-NIR range. Significant difference is seen around 550, 680, and 940 nm.

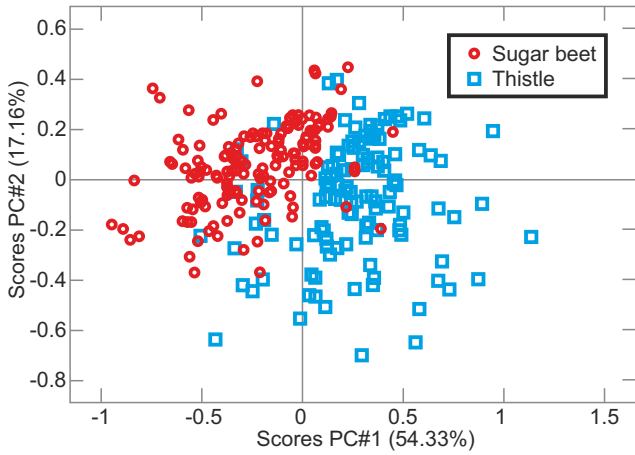


Fig. 5. Principal Component Score plot of dataset composed by 80 samples of sugar beet (red) and 80 samples of thistle (blue) plants. PC1 and PC2 accounting for the 71.5 % of the variability.

possible to distinguish different plants by identifying the spectral features where they show the maximum difference (Vrindts et al. (1998, 2002)). In the ASETA project an extensive survey of the spectra of thistles and sugar beet leaves has been conducted under real life conditions, Fig. 4 shows the average spectra of the two species.

One of the first objectives of the ASETA was to investigate the possibility of discriminating sugar beets and thistles based on their spectra under field conditions. Principal component analysis was used to assess the separability of sugar beets and thistles, and determine the most prominent features (wavebands) that show higher variability. First results show a great separation when using uncorrelated variables and indicated wavebands centered at 550, 680, 750 and 940 nm as the most significant when classifying those two species (see Fig. 5).

The aerial vision system used in this research is based on a multispectral narrow-band filter camera (seen in Fig. 2). The MiniMCA-6 (Tetracam Inc., USA) weighs 695 g

and consists of six individual digital cameras arranged in a 3 by 2 array and synchronized so they can be triggered at the same time. Each of the cameras is equipped with a 1.3 megapixel CMOS sensor. Interchangeable narrow bandpass filters are placed in front of the optics to block the unwanted frequencies. The configuration of filters (see Table 1) is selected to coincide with the wavebands where the main physiological phenomena are reflected as well as to allow the calculation of the most important vegetation indices. For technical reasons, the filters does not match the frequencies identified in Fig. 4 exactly, but are close enough for identification purposes.

Table 1. The filters mounted on the Mini MCA camera

		Mini MCA Filters					
Wavelength*	488	550	610	675	780	950	
Bandwidth*	10	10	10	10	10	40	
* nanometers							

The multiscale imaging process described in section 2.1 is used for quickly gathering information with a low resolution (approximately 50 mm/pixel), flying at high altitudes, and for a finer detection at plant level using higher resolution images (10–20 mm/pixel) taken at low altitudes.

First, a coarse vegetation map is generated from lower resolution images using the excess green index (ExG) which is highly effective in masking out the green objects from the bare soil background (Meyer et al. (2004)). A close relation exists between the mean ExG for a certain area and its vegetation density, and comparisons can be made within the same image. Regions with high biomass are ranked by importance (size and density) and geo-positioned. The traditional ExG is computed using the red, green, and blue (RGB) channels of an ordinary digital color camera. In this multispectral approach, the three channels best corresponding to RGB are used (675, 550, and 488 nm).

The information is sent to the task manager (see section 2.2) to proceed to a closer inspection for crop-weed discrimination. At low altitudes the spatial resolution increases, and the spectral mixing decreases yielding a high amount of pure pixels per plant. The crop rows are clearly seen and detected, and plants in between the rows are classified as thistles due to their position. Once classified, a library can be made with the spectral endmembers collected from the purest inter-row thistle pixels. The intra-row plants are matched with the now known endmembers and labeled as sugar beets or thistles to produce an aerial 2D weed map.

A continuous feedback is established with the UGV, which is making a more detailed characterization and estimation of weed density. This allows an online update of the relationship of mean ExG value versus plant density for the coarse aerial imaging and a supervisory update of the classification at the finer stage, which will improve the weed map even after the aerial images were taken.



(a) Sugar Beet Leaf (b) Thistle Leaf

Fig. 6. Comparison of leaf shapes and color of target species.

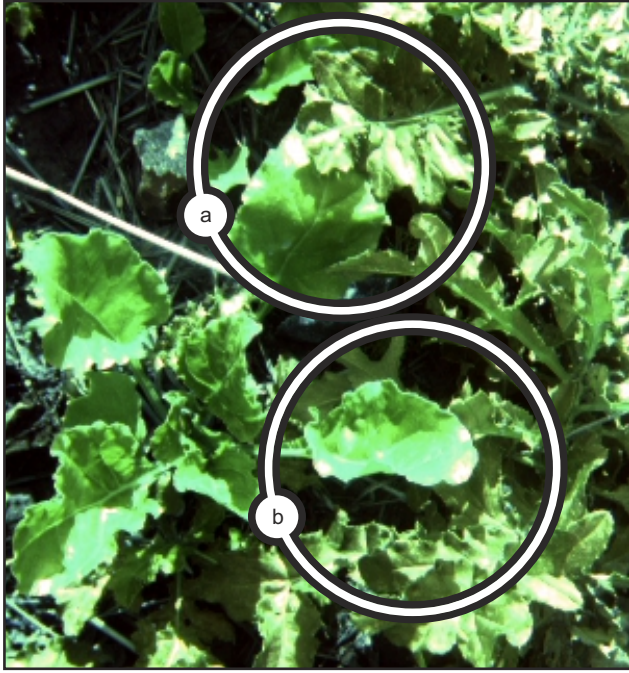


Fig. 7. Complex overlapping scenario. Thistle occluding sugar beet (a) and sugar beet without occlusion (b).

2.5 Ground vision

The analysis of aerial imagery prompts the ground vehicle for a closer inspection. In the ground based image processing, the green color of vegetation is again a first step since greenness of the plants' leaves distinguishes them well against the background soil. However, the ability to resolve overlapping leaves is limited when using 2D color imaging as it is difficult to detect whether the edge of a leaf belongs to the overlapping or the overlapped leaf. Fig. 7 shows two segments of an image. In (a), an overlapping thistle leaf has occluded the sugar beet leaf. This hides some of the features of the sugar beet leaf, and the leaf should therefore be noted as unfit for species classification. In the (b) segment, the leaf is not occluded and it is better suited for species classification.

To detect occlusions 3D imaging is better suited than 2D. Using the depth information, detecting occlusions becomes trivial. Once a leaf has been qualified for classification, either 2D or 3D imaging can be used for the further processing.

For 3D imaging, stereovision is a commonly used technique, but it suffers from correspondence and efficiency

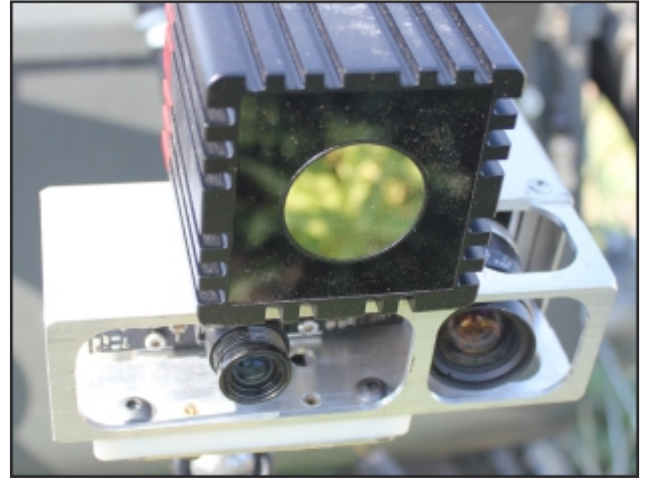


Fig. 8. Cameras mounted on Ground Vehicle. Swissranger SR4000 time-of-flight camera (top), PMD CamBoard time-of-flight camera (bottom left), and Point Grey Flea RGB camera (bottom right).

problems for close range leaf imaging. For this reason, stereovision imaging is largely limited to indoor well-lit conditions, or to an overall plant canopy measurement in outdoor conditions (McCarthy et al. (2010)).

To overcome these limitations, we are using Time of Flight (ToF) cameras along with a color camera (Fig. 8) to achieve a closer depth analysis inside plant canopies. ToF cameras are active sensors working in the Near Infrared (NIR) region. They emit infrared light and measure distances to the objects in the view based on the time it takes for the light to return.

Because the ToF cameras use NIR light, the reflectance-transmittance characteristics of the leaf surface in this spectrum must be taken into account. Any incident light is partly reflected from the leaf surface, partly absorbed and the rest is transmitted through the leaf, but only the reflected portion is interesting in ToF imaging. This topic has received a great deal of research. Jacquemoud and Baret (1990) proposed a Reflectance-Transmittance model for green leaves which show about 51% reflectance, 45% transmittance and 4% absorption for green soyabean leaves in the NIR region. Indeed, the model shows that the NIR region provides highest possible reflectance (just under 50 %) of the frequencies in the visible-NIR spectrum in the frequency band between 700 nm and 1300 nm. This fits with our observations of sugar beet and thistles shown in Fig 4. ToF cameras operating at 850 nm are hence quite suitable for plant imaging. Further, they produce depth data at more than 30 fps, while not having the correspondence or efficiency problems of stereovision.

However, ToF cameras have their own shortcomings. Other than their low resolution sensors (200x200 max), one major problem is their saturation under sunlight. In ToF cameras, integration time (IT) controls the duration for which the incoming signal is integrated onto the imaging sensor. IT must be high enough to allow sufficient depth estimation but less than the saturation threshold. The gap between these two boundaries of operation depend on the ambient light and it becomes very narrow under sunlight.

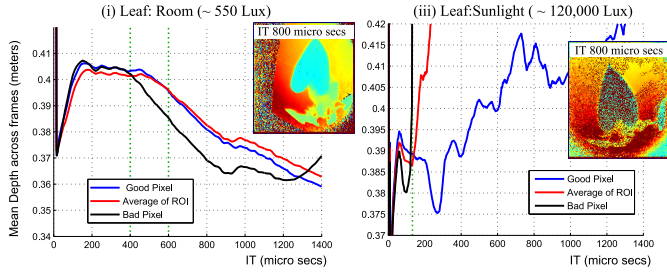


Fig. 9. Comparison of leaf imaging with PMD CamBoard ToF camera under Room and Sunlight. Two sample images at IT 800 ms illustrate the difference.

It is one of the research points of the ASETA project to look into the usefulness of ToF under these conditions.

Fig. 9 shows depth data of a single leaf under room and sunlight conditions. The graphs show the variation of depth data of two individual pixels averaged across several frames, as well as the average of their 20x20 pixel neighborhood. The pixels were located on the surface of the leaf. The point where the depth data of the pixels and the average of the neighborhood starts getting out of sync; the data is no longer reliable. This fact can render ToF cameras useless unless a shade is used to cast shadow on the view. Kazmi et al. (2012) presents a detailed analysis about leaf imaging with ToF cameras under sunlight, shadow and room conditions.

In order to classify a plant as either thistle or sugar beet, the approach is to use shape-features of the leaves (see Figs: 6(a), 6(b)) along with their relative greenness. To extract shape boundaries, an algorithm using triangular decomposition of the image similar to Distasi and Nappi (1997) is being developed. It is a generic algorithm which estimates salient regions from the edges of an object. The color channel from the color camera is mapped onto the ToF data using stereo-calibration of the two cameras. When a plant is classified, a feedback will be generated to update the weed map from aerial imagery.

2.6 Cooperation

In terms of solving the basic tasks for a crop and weed management system, the automatic planning is capable of producing the necessary waypoints for this task. However, the ASETA project attempts to push the intelligence of such a system further than basic automation and a large part of that is the cooperation between robots. One of the things being researched is how robots can cooperate with very limited communication between them. An example where this could be relevant is a farmer that has purchased a simple UAS to do mapping of his fields. After some time he purchases a newer more advanced UAS and would like them to help each other mapping the fields. The simple UAS is unable to do cooperation, but the newer UAS is capable of assisting with the mapping, simply by estimating the intentions of the older UAS from, say, ADS-B beacon data.

Currently the research focuses on how to provide a quantitative estimate of the intentions from simple beacon information. This is done using model based bayesian filtering with a short and a long term prediction. As system model,

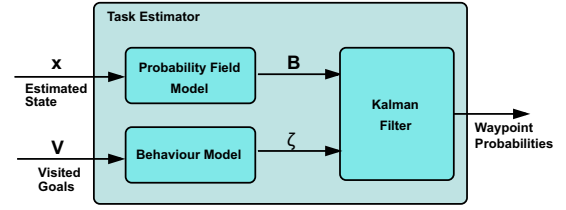


Fig. 10. Waypoint probability estimator.

a probability field mapping is used to assign probabilities to the individual waypoints depending on where they are located in relation to the motion of the helicopter. It is constructed as a dynamic function of two parts; a part called probability field map, which increases the probability for waypoints near the expected future positions of the helicopter, and a part called a dissipation function that gradually reduces the probability of all waypoints such that the waypoints need to stay within the future path of the helicopter to maintain a high probability.

The measurement model takes the information of which waypoints the agent previously have visited and from this attempts to predict the probability for each waypoint. This probability is then used as the measurement for the kalman filter which results in the measurement model matrix being the identity matrix. This prediction is done through a set of behavioral models, each modeled mathematically based on a set of assumptions. Examples of such behavioral models could be different flight patterns like a "lawnmower" pattern, a spiral pattern or a nearest neighbor pattern.

3. DISCUSSION

The ASETA project shows that it is plausible to use mobile robotics in future weed mapping and targeted weed control. At the time of writing, 8 large-scale test campaigns has been conducted in order to obtain real life images and measurements, and test the robotic platforms outside of lab-conditions. We have found that the data obtained so far in the campaigns is usable in the agricultural analyses.

While aerial imaging has been used for several years in production farming, the new platforms, brings about a range of new possibilities. Traditional aerial imaging is done using piloted planes, and the images are orthorectified, which is a rather time-consuming and expensive process that must be planned well ahead and is dependent on good weather conditions. The aerial robotic platforms provides the images whenever the farmer needs them with less dependence on weather conditions and external planning.

The ASETA project will continue to integrate the fields of agricultural image analysis and robotics, and will demonstrate a working system in 2013.

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