ROBOTIC AIRCRAFT AND INTELLIGENT SURVEILLANCE SYSTEMS FOR WEED DETECTION

Calvin Hung[1] and Salah Sukkarieh[2]
[1]Research Associate, [2]Professor, Australian Centre for Field Robotics,
The University of Sydney, NSW 2006, Australia

ABSTRACT

This paper presents a summary of the autonomous weed detection R&D program at the Australian Centre for Field Robotics (ACFR) over the past seven years. The ACFR has used various aerial robots on various detection and mapping projects, targeting weeds including prickly acacia (*Acacia nilotica*), parkinsonia (*Parkinsonia aculeata*), mesquite (*Prosopis pallida*), wheel cacti (*Opuntia robusta*) and alligator weed (*Alternanthera philoxeroides*), and extending it to include pests such as detecting Red Imported Fire Ants (RIFA) mounds, in various parts of Australia. The algorithm research at ACFR leads to various intelligent detection and mapping software systems for accurate terrain mapping, vegetation segmentation and detection of different invasive species.

Keywords: Weed detection, pest detection, robotic aircraft, intelligent systems.

INTRODUCTION

Over the last seven years the Australian Centre for Field Robotics (ACFR) at the University of Sydney has been developing robotic air vehicles and intelligent software systems for environment monitoring with particular emphasis on weed detection and eradication.

In particular, the work has focussed on developing air systems that can not only fly fixed flight paths but also use information gained from on-board sensing systems to determine optimal flight routes in real-time to maximise map and weed classification quality. These sensing systems comprise of visual, infrared, and hyperspectral reflectance and include machine learning algorithms that can build accurate terrain maps, vegetation segmentation and detect different weed species once trained. Both aquatic and terrestrial weeds were part of the studies reported here.

This paper will discuss these projects including the development and testing of the surveillance system for environment monitoring. The paper will also discuss the current system that is being trialled for operational use in weed monitoring, and future work in the area.

PROJECT SUMMARIES

ACFR has applied the weed/pest detection research on four different applications (Figure 1). Each involves different species in various environmental settings.

The woody weed detection project focused on the detection and mapping of prickly acacia (*Acacia nilotica*), parkinsonia (*Parkinsonia aculeata*) and mesquite (*Prosopis pallida*) in central Queensland (Bryson *et al.* 2010; Hung *et al*. 2012). These weeds cause significant damage to the environment by out-competing native species and reduce productivity in the farming industry through difficulty in land access and cattle mustering.

The cacti detection project focused on the wheel cacti (*Opuntia robusta*) in large area of rangelands in South Australia (Bryson and Sukkarieh 2011). The wheel cacti are drought resistant and have recently been listed in the Weeds of National Significance hit-list.

The aquatic weed detection project focused on alligator weed (*Alternanthera philoxeroides*). Alligator weed is considered one of the worst weeds due to its ability to grow both in water and on land. Alligator weed has infested small part of waterways in New South Wales, Queensland and Victoria and can cause significant amount of damage to the environment, primary industry and water infrasture if it is not controlled.

The RIFA Mound Detection project focused on the detection of Red Imported Fire Ants (RIFA) mounds near port of Brisbane (Hung and Sukkarieh 2012). RIFA can threaten local species, the bites can cause fatal allergic reaction in some people and the RIFA mounds can disrupt agricultural production.

Woody Weeds	**Cacti**	**Alligator Weed**	**RIFA Mounds**

Figure 1. Pest detection project targets

METHODOLOGY

The aerial data were collected mostly using the robotic platforms in ACFR. In each mission a region of interest with suspected pest infestation is defined. The robotic platforms then follow the predetermined flight trajectory to collect aerial images of the entire region of interest. The aerial images consist of standard Red, Green and Blue (RGB) images. For the RIFA detection mission we were also given the Infra-red (IR) and thermal bands. We used image analysis algorithms to detect and map the target distribution using the collected aerial images.

The robotic platforms and the detection algorithms are described in the following sections.

Platforms

Three ACFR aerial robotics platforms have been used in the weed detection missions (shown in Figure 2**Error! Reference source not found.**): a Hovering Unmanned Aerial Vehicle (HUAV), a scaled-down autonomous J3 Cub and a hexacopter. All platforms are equipped with camera to obtain aerial images, GPS and IMU for navigation and onboard computer for control. In addition the HUAV is equipped with a spraying system for the optional control and eradication missions.

		
HUAV	**J3 Cub**	**Hexacopter**

Figure 2. ACFR aerial robotic platforms used in pest detections

Algorithms

The intelligent software detection algorithms developed for these projects followed the same overall pipeline with interchangeable sub-components. The main stages of the piplelines are image-pre-processing, feature extraction/learning and finally detection, classification and segmentation (shown in Figure 3).

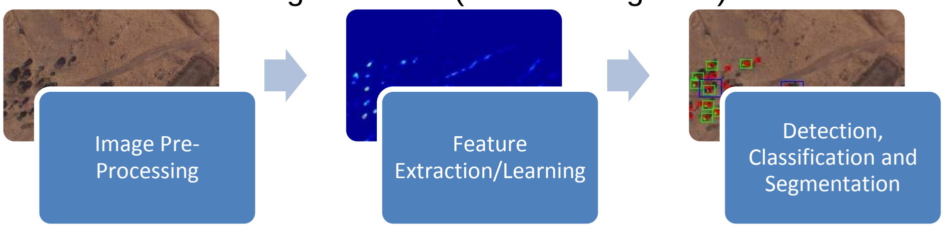


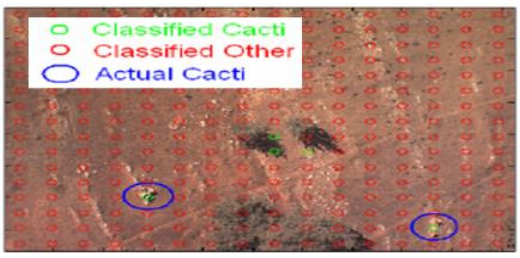
Figure 3. Detection Algorithm Overview

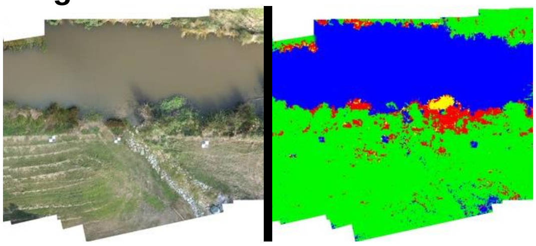
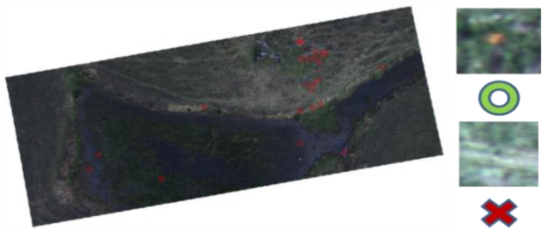
The aim of image pre-processing is to format the data that simplifies the analysis in later stages. Techniques such as noise removal, data normalisation and whitening, and the use super-pixel to group similar neighbouring pixels have been used.

The next stage is to obtain features either through selection or learning. Features are compact representations of the data. A classification algorithm typically performs better using the statistics extracted using the features instead of using the original data. In these projects standard vision features such as colour (RGB, hyper-spectral and multi-spectral channels), texture (defined by banks of Gabor filters, Laplacian pyramids) and shape (tree-crown template) have been used. In addition we have also explored the state-of-the-art feature learning techniques to obtain features that outperformed the standard feature set.

The last stage is to perform classification based on the feature responses. In the training step the classifiers take the feature response with the training label to learn a classification model, this is followed by an evaluation step before the algorithms can be applied to the rest of the dataset. In these projects we have applied various classifiers including logistic-regression classifier, support vector machines (SVM), LogiBoost and Gaussian process classifier.

Table 1. Summary of classification and segmentation results.

Woody Weed Detection	**Cacti Detection**
 Achieved an overall accuracy of 95%. (Hung 2013, p. 126)	 Achieved an overall accuracy of 84%. (Bryson and Sukkarieh 2011)

Alligator Weed Detection	RIFA Mound Detection
	
Preliminary results from the Victoria field trial 2013.	Achieved an overall accuracy of 89%. (Hung and Sukkarieh 2012)

RESULTS AND DISCUSSION

The classification and segmentation results of the projects are shown in Table 1.

CONCLUSIONS AND FUTURE WORK

In the past seven years ACFR has developed a system for the environmental surveying missions, from the aerial robots used to collect the aerial imagery autonomously, to the intelligent software pipeline to detect and map the target weed/pest from the aerial images. This system has been applied to four different projects in various parts of Australia and the research has shown state-of-the-art detection and classification results that could be beneficial to the local communities.

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