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A Rotary-wing Unmanned Air Vehicle for Aquatic Weed Surveillance and Management

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Abstract This paper addresses the novel application of an autonomous rotary-wing unmanned air vehicle (RUAV) as a cost-effective tool for the surveillance and management of aquatic weeds. A conservative estimate of the annual loss of agricultural revenue to the Australian economy due to weeds is in the order of A$4 billion, hence the reason why weed control is of national significance. The presented system locates and identifies weeds in inaccessible locations. The RUAV is equipped with low-cost sensor suites and various weed detection algorithms. In order to provide the weed control operators with the capability of autonomous or remote control spraying and treatment of the aquatic weeds the RUAV is also fitted with a spray mechanism. The system has been demonstrated over inaccessible weed infested aquatic habitats.

Keywords Rotary-wing unmanned aerial vehicle (RUAV) · Civilian UAV applications · Ecological research · Weed surveillance · Weed management

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1 Introduction

Weeds are one of the most serious threats to the Australian ecological environment, to rangelands and primary production industries. Weeds hinder the growth of the native species, cause land degradation, and reduce farm and forest productivity. A conservative estimate of the annual cost of weeds to the Australian economy as loss in agricultural revenue is in the order of A$4 billion [1]. Apart from the economic impact weeds also have an adverse affect on the surrounding fauna, flora, biodiversity, native landscape, irrigation, and any supporting tourism. Hence the reason why weed control is of national significance.

An unmanned aerial system (UAS) has been developed as a cost-effective tool for the surveillance and management of weeds. The UAS consists of a rotary-wing unmanned aerial vehicle (RUAV) equipped with a navigation subsystem, a control subsystem, an image acquisition subsystem, a spray mechanism, a ground station, a communication subsystem, and a surveillance data processing subsystem with aquatic weed detection algorithms.

The paper is organised as follows: Section 2 examines related works. Section 3 briefly explains what a weed is in our context, and which weeds we are going to address in our work. Section 4 explains the sequence of the operational processes of a typical aquatic weed surveillance and management mission. Section 5 presents the overall system architecture and explains the primary subsystems. Section 6 provides examples from our field trials. Section 7 presents the weed detection, classification and mapping algorithm. Section 8 addresses the georeferencing process. Finally, Section 9 draws the conclusions and addresses future work.

2 Related Works

Although unmanned aerial vehicles (UAVs) have been used for military applications since the First World War [2], their civilian applications [3–5], particularly their use in agriculture [6], rangeland and ecological research [7] is relatively new. The high cost of the UAV platforms, safety concerns, and the need for specialised operating personnel are some of the major reasons behind the delayed introduction of UAVs to ecological research. The increasing availability of more reliable and low-cost UAV platforms offers new possibilities.

Aerial photography is the most common UAV application in rangeland and ecological research. The UAVs used in these application varies from low-cost model aircrafts [8] to custom built, state-of-the-art aerial platforms [6, 9].

As a low-cost solution, a commercial-off-the-shelf (COTS), prebuilt airframe of a radio-controlled (RC) model aircraft has been demonstrated in [8] for aerial rangeland photography. This platform was selected for its slow flight speed and inherent stability. The model was fitted with a COTS flight stabiliser, a barometric altitude-hold module from the RC hobby sector, a single-lens reflex (SLR) camera, and a global positioning system (GPS) receiver for geolocation of the aerial photos. Although the model aircraft was lacking an autopilot and on-board navigation unit for accurate attitude determination it was demonstrated that even low-tech solutions can be useful for some applications.

At the other extreme, [6, 9] addresses precision agriculture using a solar-powered, Pathfinder-Plus UAV developed by NASA and AeroVironment. This high-tech, high-altitude flying UAV is equipped with multispectral and hyperspectral imaging systems and was demonstrated over the Kauai Coffee Plantation.

The above mentioned works focused on the surveillance of large rangelands. The work presented in this paper differs in that the RUAV is not only used for aerial imagery of weed infested aquatic habitats, but also for spot spraying the designated locations. Furthermore, the presented work incorporates an automated weed detection and classification algorithm as well.

Another distinguishing factor is that the RUAV has multiple modes of operations: manual control mode, semi-autonomous, and autonomous flight modes. Although the current aviation safety rules in Australia limit the RUAV operations to be performed only by qualified UAV operators, the flexibility in proving various operational modes increases the future possibility of operating the RUAV without specialised UAV personnel.

Remote sensing and satellite imagery have been used in environmental research for a long time. Typical satellite imagery available to the civilian domain has approximately 15–45 m resolution per pixel. These images are useful for a high level overview of very large landscapes.

Remote sensing data from human piloted aircrafts can provide better than 1 m spatial resolution imagery. This is useful for providing ground truth for the satellite data as well as investigation of relatively large rangelands. Although, it is possible to acquire even higher resolution imagery from human piloted aircrafts by using higher resolution cameras and flying at lower altitude, these options introduce their own draw backs and in particular safety concerns as human piloted aircrafts cannot safely operate in narrow corridors around natural obstacles such as valleys, trees or bushes, even if ultralight aircrafts [10] are used.

Hence, when centimetre or better resolution is desired from aerial imagery, UAVs can provide an effective *close sensing* solution without putting human operators into risk.

3 What is a Weed?

Weeds are rapidly spreading invasive plants which have an adverse effect on the environment and can have serious economic impact. Although some native plants can also become weeds if the right conditions arise, the overwhelming majority of weeds in Australia are those which are introduced into Australia from other continents, mainly due to human activity.

In our work we have focused on alligator weed and salvinia. Both of them are considered as "Weeds of National Significance", because of their devastating impact to the environment and economy. Figure 1 shows examples from alligator weed and salvinia infested aquatic habitats.

3.1 Alligator Weed

Alligator weed (*alternanthera philoxeroides*) [11] is a native plant of the Parana River system in north-eastern Argentina. It was first reported in Australia in the 1940s and

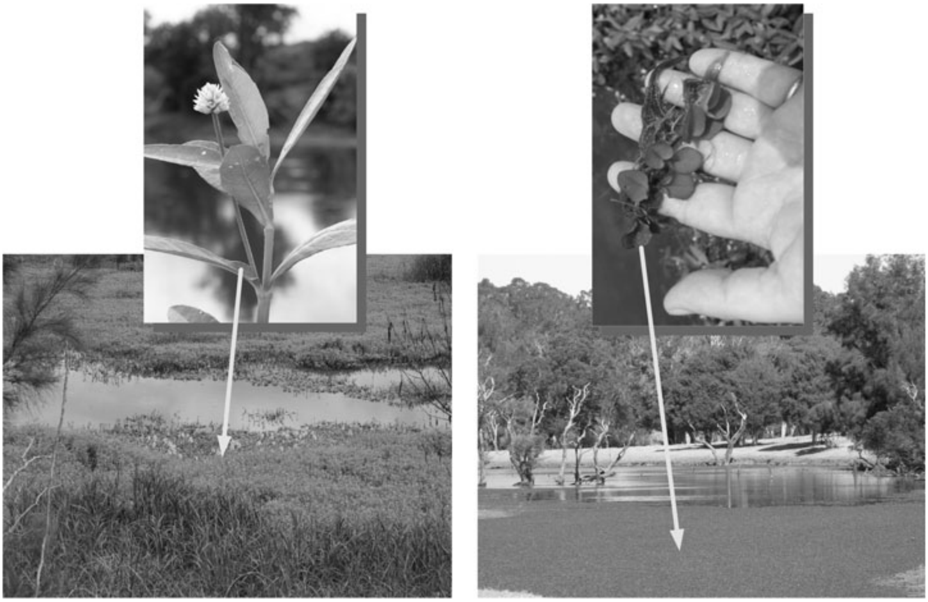

Fig. 1 "Weeds of National Significance"; (left image) an irrigation channel blocked by Alligator Weed (*alternanthera philoxeroides*), (right image) a pond severely covered by Salvinia (*salvinia molesta*)

believed to have been introduced in shipping ballast. Alligator weed continues to threaten to spread along the east coast of Australia.

Alligator weed is extremely invasive, and a has high potential for rapid spread to large areas. Furthermore it can also invade both aquatic and land habitats. Control of alligator weed is very hard and has a very high economic and environmental impact.

3.2 Salvinia

Salvinia (*salvinia molesta*) [11] originated from south-east Brazil as an aquarium plant and was first recorded in Australia in 1952. Salvinia can cause devastating and severely affect riparian ecosystems, water quality, wildlife and the surrounding primary industries.

Given the right conditions salvinia exhibits an extraordinary growth rate; it can double its dry weight in two and a half days. With such a growth rate it does not take too long to block waterways, irrigation channels, smother dams and reservoir surfaces. The sun light cannot penetrate the salvinia covered layer. This eventually causes the underwater plants and the fauna to die. Holm and East-West Center [12] describes salvinia as one of the world's worst weed.

4 Aquatic Weed Surveillance and the Management Process Flow

We performed our early RUAV based aquatic weed surveillance and management demonstrations over a weed infested aquatic habitat near the Richmond area, north-west of Sydney in 2008. These areas are often closed-off by dense bushes and known for the spread of alligator weed and salvinia. Snakes, spiders and other dangerous animals add extra difficulties for human access for surveillance and management of weeds. In practical terms these habitats are inaccessible neither from the ground or through water ways and so consequently weeds flourish.

As shown in Fig. 2, a typical weed surveillance mission starts with some a-priori estimate of the weed location given by human weed experts. These initial estimates are often based on a geographical information system (GIS), environmental conditions, weed sightings, and/or data from satellite imagery, aerial imagery obtained from manned flights, but above all, it is based on the tacit knowledge of the subject matter experts with years of experience in the field.

Based on the draft situation model and environmental constraints, such as topography of the region, obstacles, wind directions and so forth, flight plans are prepared on the ground and uploaded to the RUAV autopilot for autonomous surveillance. Alternatively, a human pilot remotely controls the RUAV to visit the suspected regions for data collection.

The collected data is then uploaded to a ground based computer for weed detection, classification, and mapping process. Human experts do play a major role and supervise the computer algorithms for the detection and classification of the weeds. A number of different machine learning techniques are being studied. The current version of the weed detection and classification system is based on Support Vector Machines (SVM) which are used to create weed infestation maps that is fed back to the GIS and weed authorities for future planning.

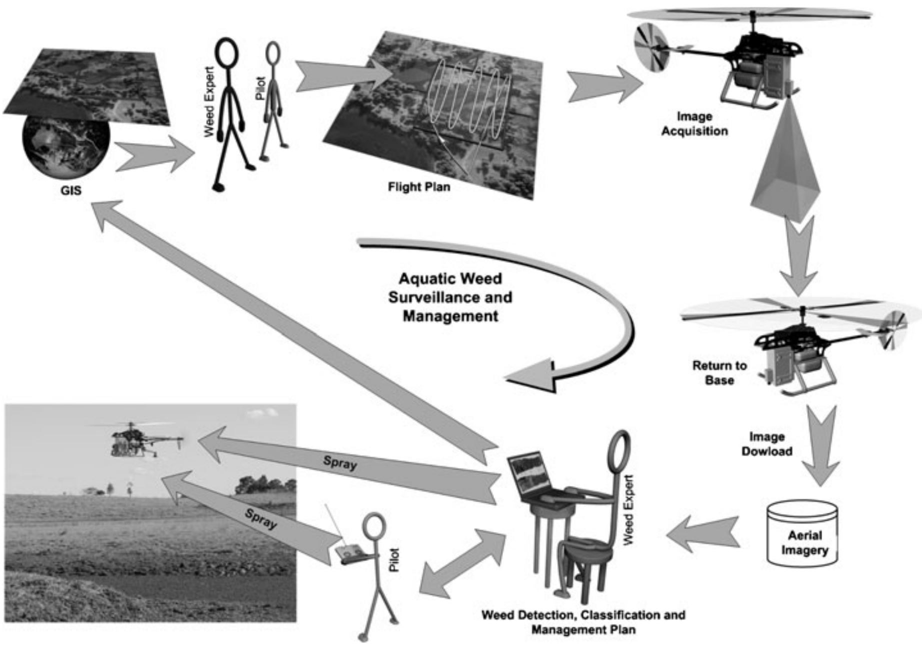

Fig. 2 Aquatic weed surveillance and management process flow

Once the weed infested regions are mapped, human experts' are then used to define potential points for the RUAV to spot spraying. Current civil aviation rules and regulations imposed by the Australian Civil Aviation and Safety Authority (CASA) have tight restrictions on the spraying of chemicals from aircrafts. The relevant acts provide details about the endorsement of the aircraft and the human pilot for the spraying operations. Obviously these rules cannot be applied directly to unmanned operations. Therefore in order to demonstrate the proof-of-concept of using the RUAV for weed control in our experiments without infringing the laws we used water soluble non-toxic dye instead of real herbicides.

5 Architecture

This section describes the hardware and software architecture of the RUAV. As shown in Fig. 3 the RUAV is fitted with a navigation computer, a vision sensor computer, and an autopilot module. The navigation sensor computers are both in PC/104-*Plus* form factors, and the autopilot module is built around an embedded microcontroller board. They are linked together with an onboard network and they are also able to communicate to the ground control station (GCS) via the communication subsystem.

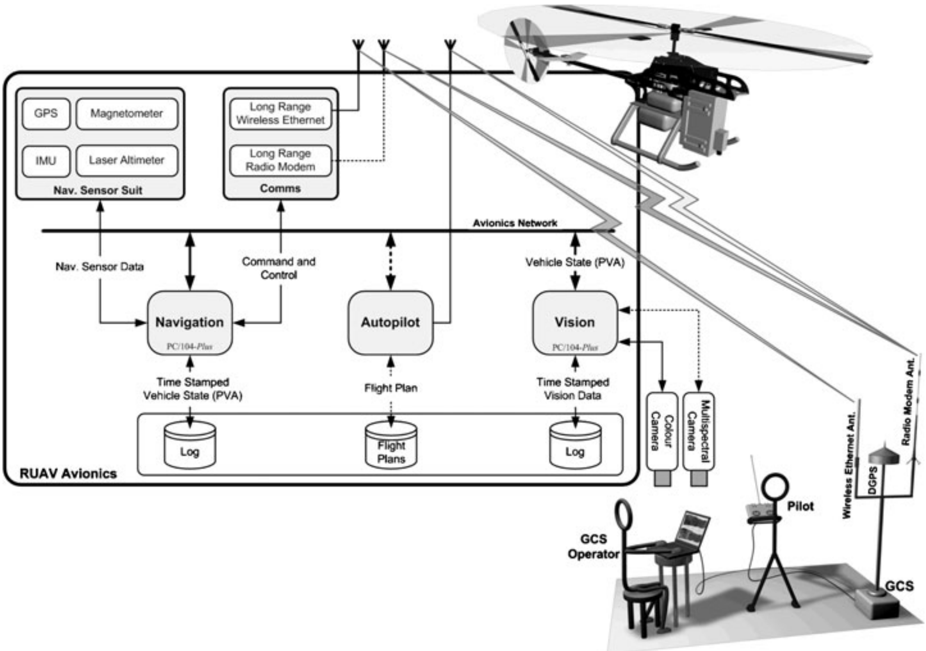

Fig. 3 Representation UAS and the avionics architecture of the RUAV used in the aquatic weed surveillance and management demonstrations

5.1 RUAV Avionics

5.1.1 Navigation Subsystem

In order to accurately localise and georeference the weeds and other feature of interests (FoI) in the aerial imagery an accurate estimate of the RUAV position and attitude are needed. In our system architecture the navigation computer provides this estimate at rate of up to 20 Hz.

As illustrated in Fig. 3 the navigation subsystem is connected to navigation sensor suite. It consists of a Novatel OEM4-GSL-RT20 [13] global positioning system (GPS) receiver, an inertial measurement unit (IMU), a Honeywell HMR2300 [14] magnetometer which provides high accuracy magnetic heading information, and a downward pointed MDL LaserACE IM35 [15] laser range finder for determining height above ground.

The navigation computer reads the sensor data and calculates the navigation solution. Both the raw sensor data and the navigation solution is logged on an onboard disk. All the logged data is accurately time stamped for further analysis. The navigation solution is also published onto the avionics network for other subsystems.

The navigation data is also available to the ground control station (GCS). The GCS uses the navigation solution to update the GCS screen at real-time to indicate the position and attitude of the RUAV to maximise the situation awareness of the GCS operator and the pilot.

5.1.2 Image Acquisition Subsystem

Early in the project many experiments were conducted to test various ideas on the type of sensors and the detection algorithms. This information was needed to determine the physical size and weight of the surveillance system which in turn governed how it would be mounted on the RUAV. A number of colour cameras and multi-spectral cameras with infrared (IR) and near-infrared (NIR) bands were investigated. Finally, the Hitachi HV-F31 progressive scan 3 CCD [16] camera was selected.

The image acquisition subsystem consists of a PC/104-*Plus* computer and a digital video camera interfaced to each other via IEEE 1394 (FireWire). The Hitachi HV-F31 has 1028×764 pixel spatial resolution and provides separate Red, Green, and Blue frames.

A Fujinon Lens TF4 DA-8 with 4 *mm* focal length is attached to the camera. This configuration gives a field of view of approximately 60° in the horizontal and 40° in vertical directions. The image acquisition computer is mounted inside the payload box and the camera is mounted to the forward faced surface looking down. Figures 3 and 4 illustrate the position of the camera and its relative orientation with respect to the RUAV body.

The image acquisition subsystem is configured to capture at 3 frames per second. The captured images are saved onto the onboard disk with a high resolution time stamp. The time stamp information is later used to match the navigation solution record for geo-referencing of the image frame as well as geo-referencing the detected weed in the frame.

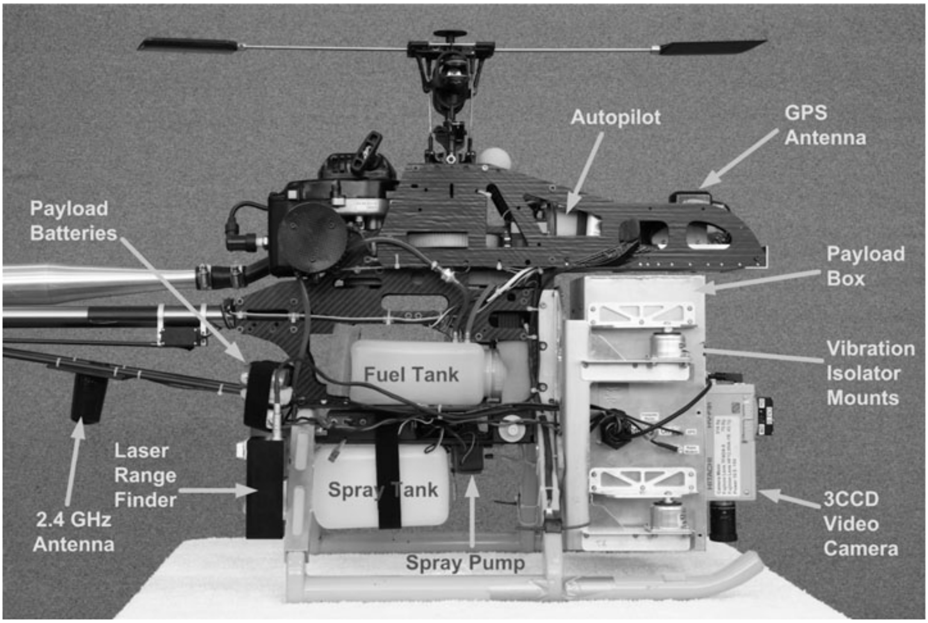

Fig. 4 Close-up view of the RUAV frame with the payload box and onboard electronics

The changing of the camera unit with another IEEE 1394 compatible camera is a relatively straight forward operation in terms of software configuration and/or modification. However, physical size, weight and the electrical power consumption of the new camera has to be examined carefully.

5.1.3 Autopilot Subsystem

The objective of the autopilot subsystem (flight control subystem) is to provide a stabilised platform that could then be commanded to move to defined locations. We used a COTS, European made autopilot unit. This unit had its limitations and problems which only became apparent after testing.

With this flight control system (Fig. 4) the platform could be commanded to move along straight line paths to geo-referenced way points. This way the operations were conducted to suit its limitations. This impacted on what could be achieved in terms of flight regimes. For example, we were confident in flying straight channels, or over large open spaces, but less confident in following a tight meandering river. Even though we were not aiming to conduct experiments which involved difficult spraying manoeuvres or to follow tight curves, it was something that we hoped to test. This did not affect the surveillance system or its results.

5.1.4 Communication Subsystem

The current payload box is designed to accommodate mainly two different type of COTS communication units; a 2.4 *GHz* spread spectrum, long-range wireless

Ethernet transceiver or a 900 MHz long range radio modem. Depending on the bandwidth requirements of the data down-link either of these communication units can be used.

Figure 4 shows a configuration of the RUAV carrying a 2.4 GHz antenna. In our current configuration all interaction between the GCS and the onboard navigation and vision computers occurs over the 2.4 GHz wireless Ethernet link. The autopilot module illustrated in Fig. 3 uses its own in-built transceiver to communicate with the GCS terminal.

5.2 The RUAV Platform

The first prototype of the RUAV was based on the G18 Industrial Helicopter which was designed and manufactured in Australia. A range of major modifications have been made to increase the reliability, endurance, and payload capacity. Using an Australian manufacturer allowed us to easily liaise with the manufacturer to modify the helicopter for our specific requirements.

An on board telemetry system was also added to enable us to monitor parameters which were important to the health of the system. These included temperatures, voltages and rotor RPM.

The basic specifications of the RUAV platform are:

Overall Length: 2.0 m
Overall Height: 0.63 m
Main Rotor Diameter: 1.8 m
Max Take Off Weight: 15 kg
Engine: 26*cc* *Zenoah* (modified)
Speed: 0 to 100 km/h
Endurance: 20 min to 2 h (payload dependant)

The front payload area was modified to accommodate our navigation, autonomous flight control system and associated vibration isolation mounts. Additional mounting points were also installed for the GPS antenna, the magnetometer and the communications antenna.

A new payload mounting system was added to the front of the helicopter to allow the installation of our camera system, its associated imaging processing equipment and the radio communications system. This required a complex vibration isolation system to reduce the vibration to an acceptable level for the camera system and prevent motion blur of the images. The isolators had to be symmetrically located around the centre of gravity of the payload to ensure the rolling and pitching motions were not introduced by the vibration. This added significant weight to the helicopter. Further development of this mount would reduce its weight and increase the duration of the RUAV.

Additional mounting points were installed in the undercarriage legs to allow a spray boom to be attached to each side of the helicopter. A controlled droplet applicator (CDA) was attached to the end of each boom. The boom design was modified to reduce vibration caused by the rotor down draft. Ball joints were installed and the boom hinges to allow for movement of the spray booms when in contact with the ground during takeoff and landing.

A mounting tray was designed and attached to the underside of the fuel tank. This contained the spray liquid tank, spray pump, control system and power supply. The spray tank was located under the centre of gravity of the helicopter so it did not effect the balance as the spray liquid was used. For demonstration purposes a dye was added to water to enable visualisation of the spray patterns and area covered.

The modified platform proved to be very robust. The spray mechanism can be seen in Fig. 5 during a flight test of the RUAV. Figure 4 shows a close-up view of the main body and major components of the RUAV.

The actual configuration of the helicopter depended on the mission required for each area of research. Initially the navigation and autonomous flight control system, the imaging system and the spray system were all tested individually. The imaging system and spray system were then combined with the flight control system for autonomous operations.

For demonstration purposes the helicopter was flown with the imaging system and spray system simultaneously. This configuration had an endurance of approximately 30 min. A commercial system would most likely be reconfigured to have two helicopters, one for weed detection and another for spraying.

This would increase the endurance of the detection helicopter to approximately 2 h with the current imaging system and more with a purpose designed system. The

Fig. 5 The RUAV during hovering over a weed patch at the University of Sydney's flight test facility at Marulan ($34°35'40''S$, $150°3'19''E$) New South Wales, Australia

spraying helicopter could then carry in excess of four litres of spray and would only be required to operate if weeds were detected.

6 Field Trials

The pre-mission testing of the system was done at the University of Sydney's flight test facility at Marulan ($34°35'40''S$, $150°3'19''E$) New South Wales, Australia. Multiple flight tests were conducted to determine the stability of the platform as well as ensuring that all electronics could handle the vibration environment of the system. As expected each flight test taught us something new about the system and its capability eventually leading to the working system. Figure 5 shows the RUAV in flight at Marulan, carrying a gimbal unit and the sprayer mechanism.

We performed our first set of weed detection trials at the Killarney Chain of Ponds in Pitt Town. Figure 6 shows a typical panoramic view from the ponds. This area is known for its spread of Alligator weed and Salvinia.

The trial was conducted on April 2008 on one of the farms that we had access to where only Alligator Weed was available. Figure 7 shows an instance from these tests. The system worked as planned, being able to fly around the aquatic site, collect imagery, communicate to the ground station, and spray water soluble dye at designated locations to simulate application of herbicide.

A set of experiments were also conducted in August 2008 at around the same region where the weeds were already sprayed by a local contractor. The test conducted with the detection focussed on classifying "sprayed Salvinia". Thus, the only theoretical difference to a normal outbreak would be the colour and a slight change in texture. The results for Salvinia look promising although more work is required when the weed is in its active period. It was also a successful trial, demonstrating that the system could fly along the creek, detect and spray. The project demonstration video can be seen on [17].

Fig. 6 A stitched panoramic view of an aquatic weed infestation of a water way at the Killarney Chain of Ponds in Pitt Town north-west of Sydney, Australia

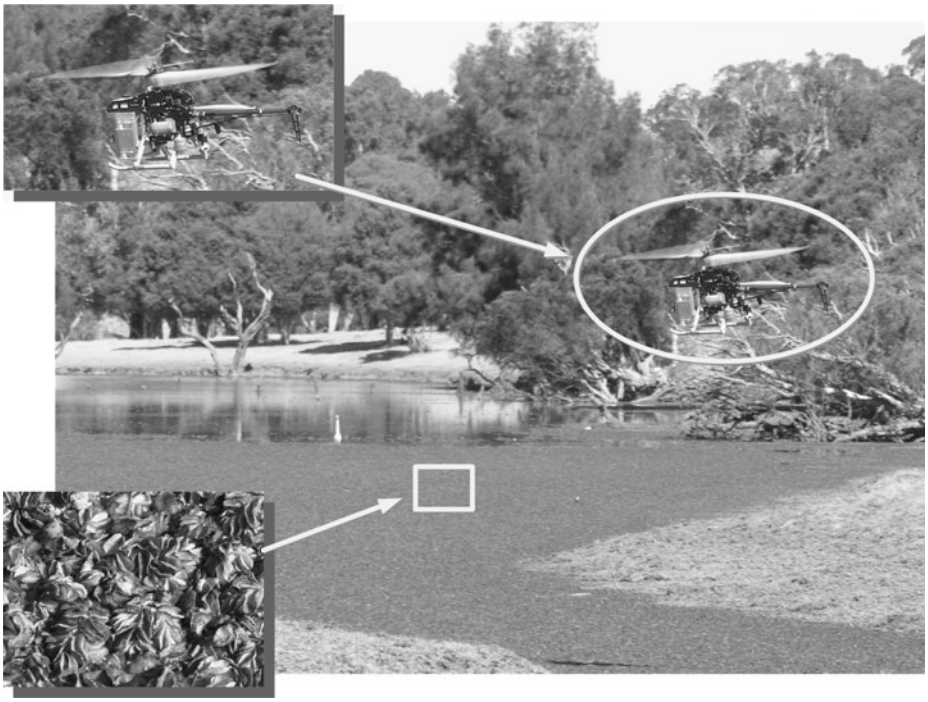

Fig. 7 The RUAV fying (*upper inset*) over the Salvinia infested habitat (*lower inset*)

7 Weed Detection, Classification and Mapping

As was highlighted in Section 4, a weed experts' input into the weed detection, classification and mapping process is an important requirement for our work. In order to utilise the tacit knowledge of weed experts we concentrated on using supervised machine learning techniques.

Figure 8 illustrates the role of the human weed expert in supervision of the weed detection and classification process. The human weed expert uses the aerial imagery of the weed infested habitats and interactively highlights a number of small regions as features of interest (FoI). The supervised machine learning algorithm takes these samples and processes the rest of the imagery to detect the same or similar FoIs. It reports its findings back to human expert as probability distributions.

7.1 Support Vector Machine

We have investigated and applied a number of machine learning techniques. Our initial experiments with the Support Vector Machine (SVM) provided promising results. There is also literature in which SVM was used in ecological research [18].

The aim of SVM is to construct a hyperplane H used to separate two classes of data points with maximum margin [19–21]. The margin is maximised by using two parallel hyperplanes H_1 and H_2 pressing against the most outlying data points from

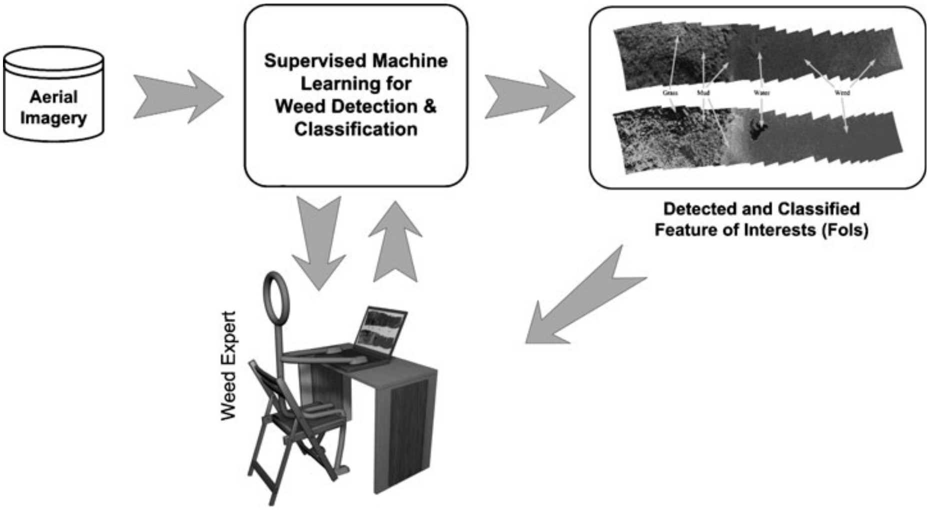

Fig. 8 The process of supervised machine learning to weed detection and classification

each class during the training process, these points are therefore called the support vectors.

For data points to be in class one, they must sit above the hyperplane H_1, and for points to be in class two they must lie below hyperplane H_2. These are the constraints of the problem (Fig. 9).

$\mathbf{x} \cdot \mathbf{w} + b \geq +1,\ y_i = +1$ and $\mathbf{x} \cdot \mathbf{w} + b \leq -1,\ y_i = -1$. These constrains can be combined into one single constraint

$$y_i(\mathbf{x} \cdot \mathbf{w} + b) - 1 \geq 0, \forall i \tag{1}$$

Also, maximising the margin $\frac{2}{\|\mathbf{w}\|}$ is equivalent to minimising $\|\mathbf{w}\|$. This is an optimization problem and can be solved using the Lagrangian Formulation.

$$L_P(\mathbf{w}, b, \alpha) = \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^{l} \alpha_i y_i (\mathbf{x_i} \cdot \mathbf{w} + b) + \sum_{i=1}^{l} \alpha_i \tag{2}$$

$$L_D(\alpha) = \sum_{i=1}^{l} \alpha - \frac{1}{2} \sum_{i=1,\, j=1}^{l} \alpha_i \alpha_j y_i y_j \mathbf{x_i} \cdot \mathbf{x_j} \tag{3}$$

Equation 2 is the Lagrangian in Primal Form, whereas Eq. 3 is the Lagrangian in Dual Form. The value of α is solved in Lagrangian Dual form, then the hyperplane parameters w and b can be solved in the primal form during the training process. With all the available parameters, the classifier is defined as:

$$f(\mathbf{x}) = sgn\left(\sum_{i=1}^{l} y_i \alpha_i (\mathbf{x_i} \cdot \mathbf{w} + b)\right) \tag{4}$$

However, this classifier can be only used on the linearly separable problems. To solve more complicated problems, kernels can be used to transform the original

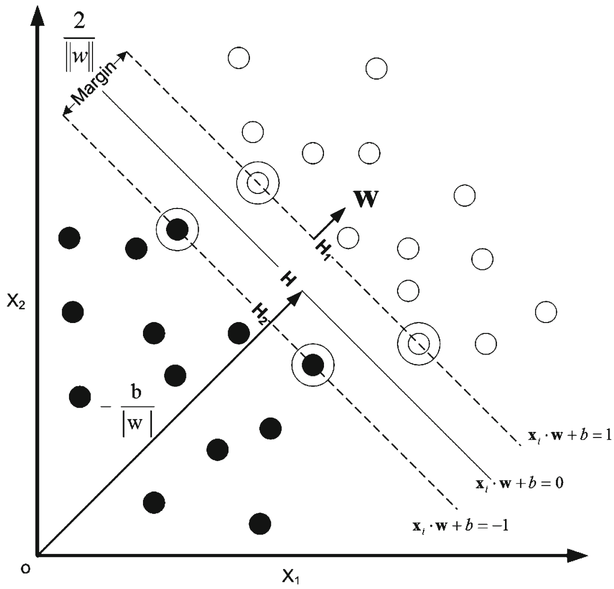

Fig. 9 The principles of support vector machines (SVM)

data from input space to higher dimensional feature space where the data points are separable. The most widely used kernels are shown in the following table (Table 1):

$$f(\mathbf{x}) = sgn\left(\sum_{i=1}^{l} y_i \alpha_i K(\mathbf{x}_\mathbf{i}^\mathbf{s}, \mathbf{x}) + b\right) \tag{5}$$

The classifier with the kernel is given in Eq. 5.

The advantages of SVM are its ability to use kernels to solve non-linear problems. Also there are no local minima, the optimaisation solution is always global and unique. The disadvantage of SVM is that there is no systematic method of choosing the kernel parameter.

The detection algorithm is based on maximum margin classification. A large data set comprising of $n \times n$ pixels of imagery taken from the camera is collected and the set separated manually into what is and what is not a weed. Each $n \times n$ pixel is in itself marked as an image of p dimensions. In particular these dimensions take into consideration colour, shape and texture. The classification algorithm then tries to determine a hyperplane which separates the images into the two sets; this hyperplane becomes the detection model. Thus any new data that comes in is passed through this model and will fall on either side of the hyperplane depending on whether it is or is

Table 1 Commonly used kernel and the corresponding classifier [20]

	Kernel	Classifier
$K\left(\mathbf{x}_\mathbf{i}^\mathbf{s}, \mathbf{x}\right) = \left(\mathbf{x}_\mathbf{i}^\mathbf{s} \cdot \mathbf{x} + 1\right)^p$	Polynomial kernel	Polynomial learning machine
$K\left(\mathbf{x}_\mathbf{i}^\mathbf{s}, \mathbf{x}\right) = exp\left(-\frac{\left\|\mathbf{x}_\mathbf{i}^\mathbf{s} - \mathbf{x}\right\|^2}{2\sigma^2}\right)$	Gaussian kernel	Radial basis function network
$K\left(\mathbf{x}_\mathbf{i}^\mathbf{s}, \mathbf{x}\right) = tanh\left(\kappa \mathbf{x}_\mathbf{i}^\mathbf{s} \cdot \mathbf{x} - \delta\right)$	Tangent hyperbolic kernel	Two layer neural network

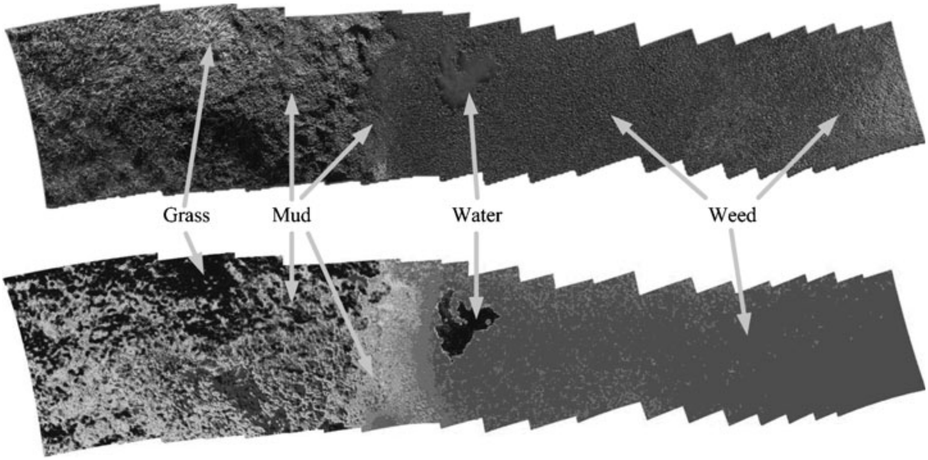

Fig. 10 Using SVM to detect weed infested regions. The *image at the top* is a stitched mosaic of airborne images. The *image in the bottom* is the probability distribution of the weeds

not a weed. Depending on how far the image fits away from the hyperplane will determine the probability that the image is within that set.

The upper section of Fig. 10 shows the weeds, water, grass and mud covered regions in a stitched mosaic of airborne images captured by the RUAV. The lower part of the same figure indicates the probability of being weed or not weed. This

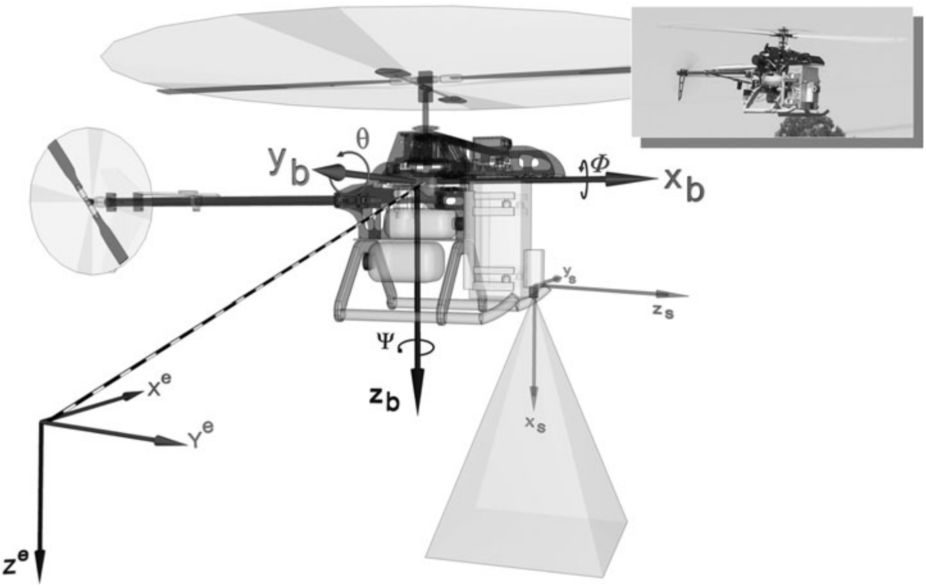

Fig. 11 The body-fixed frame reference, and the sensor-fixed frame reference of the fixed camera system. The *inset* shows the RUAV in flight carrying down-looking camera

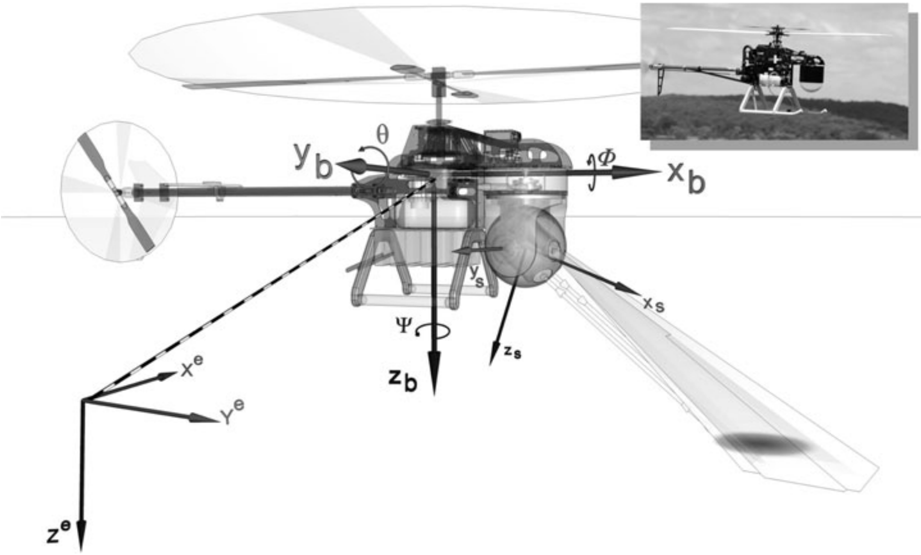

Fig. 12 The body-fixed frame of reference, and the sensor-fixed frame reference of the gimballed vision sensor. The *inset* shows the RUAV in flight, carrying a gimbal mechanism

binary grouping simplifies the spraying decision. Red colored regions indicates the high confidence in the detection of weed. The algorithm proved to be very robust and reliable. The $LIBSVM$ [22] library, an integrated implementation of the SVM is utilised in the classification and detection processes.

8 Georeferencing

Once the FoIs and the weed infested regions are located in the image frames, the next process is to determine their global coordinates so that RUAV spray mission plans can be prepared.

Geo-referencing of airborne imagery is a well studied field. The geo-referencing and rectification of images acquired with remotely operated RC model airplane is briefly explained in [23]. Similarly in [24] shows the process of geo-referencing of airborne imagery from multiple cameras.

Figures 11 and 12 illustrate the coordinate transformations on the body-fixed camera and on the gimballed camera systems used for the airborne *close sensing* weed imagery. The detailed formulation of geo-referencing process is given in [25].

9 Conclusion and Future Works

This paper presented a novel ecological research application of a UAS. A remotely controlled RUAV with optional live video and telemetry feed back to the human operators was shown to be effective to reach inaccessible, weed infested aquatic habitats. For beyond line-of-sight operations a RUAV with autopilot and online decision making system is required.

We have investigated and applied a number of machine learning techniques. Our initial experiments with the Support Vector Machine (SVM) provided promising results. However we will continue to work in machine learning domain and improve our system further.

The presented system well performed in detection, classification and mapping of alligator weed and salvinia. Both of these weeds are considered as "Weeds of National Significance". The tacit knowledge and expertise of the human weed experts are successfully incorporated into the decision making processes [17].

Possibilities of utilisation of the multi-spectral and hyper-spectral sensors will be investigated in future work.

Using autonomous RUAVs for the aquatic weed surveillance and management has shown to produce promising positive outcomes for the natural environment.

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References

1. Australian Government: Department of Agriculture, Fisheries and Forestry, "Contours". ISSN:1447-9087 (2007)
2. Cook, K.L.B.: The silent force multiplier: the history and role of UAVs in warfare. In: IEEE Aerospace Conference (2007)
3. Dossier: Civilian applications: the challenges facing the UAV industry. Air Space Eur. **1**(5–6), 63–66 (1999)
4. Cox, T.H., Nagy, C.J., Skoog, M.A., Somers, I.A.: Civil UAV capability assessment (draft version). NASA Capability Assessment Report (2004)
5. Task-Force: UAV, a concept for European regulations for civil unmanned aerial vehicles (UAVs). The Joint Aviation Authorities(JAA)/AuroControl Initiatie on UAVs (2004)
6. Herwitz, S.R., Johnson, L.F., Arvesen, J.C., Higgins, R.G., Leung, J.G., Dunagan, S.E.: Precision agriculture as a commercial application for solar-powered unmanned air vehicles. In: AIAA's 1st Technical Conference and Workshop on Unmanned Aerospace Vehicles, AIAA 2002–3404, 7 pp. (2002)
7. Rango, A., Laliberte, A., Steele, C., Herrick, J.E., Bestelmeyer, B., Schmugge, T., Roanhorse, A., Jenkins, V.: Research article: using unmanned aerial vehicles for Rangelands: current applications and future potentials. Environ. Pract. **8**, 159–168. ISSN:1466-0466 (2006)
8. Hardin, P.J., Jackson, M.J.: An unmanned aerial vehicle for Rangeland photography. J. Rangeland Ecol. Manage. **58**(4), 439–442 (2005)
9. Herwitz, S.R., Johnson, L.F., Dunagan, S.E., Higgins, R.G., Sullivan, D.V., Zheng, J., Lobitz, B.M., Leung, J.G., Gallmeyer, B.A., Aoyagi, M., Slye, R.E., Brass, J.A.: Imaging from an unmanned aerial vehicle: agricultural surveillance and decision support. J. Comput. Electron. Agric. **44**(1), 49–61 (2004)
10. Grigg, G.C., Pople, A.R., Beard, L.A.: Application of an ultralight aircraft to aerial surveys of kangaroos on grazing properties. J. Wildl. Res. **24**, 359–372 (1997)

11. Sainty, G.R., Jacobs, S.W.L.: Waterpants in Australia, 4th edn, 416 pp. Sainty and Associates Pty. Ltd., Sydney. ISBN:0-9581055-1-0 (2003)
12. Holm, L.G., East-West Center: The world's worst weeds: distribution and biology, vol. xii, 609 pp. Honolulu: Published for the East-West Center by the University Press of Hawaii. ISBN:0824802950 (1977)
13. Novatel OEM4-GSL-RT20: http://www.novatel.com/Documents/Papers/oem4g2.pdf. Retrieved 26 Feb 2008
14. Honeywell: HMR2300 smart digital magnetometer. http://www.ssec.honeywell.com/magnetic/datasheets/hmr2300.pdf. Retrieved 26 Feb 2008
15. MDL Laser ACEIM35: The laser, IM OEM laser modules. http://www.mdl.co.uk/laser_modules/laserace-im/index.html. Retrieved 26 Feb 2008
16. Hitachi Kokusai Electric Inc.: HV-F31 progressive scan 3CCD camera. http://www.hitachidenshi.com/supportingdocs/.../.../microscope_medical/HVF31.pdf. Retrieved 26 Feb 2008
17. Sukkarieh, S., Bryson, M., Göktoğan, A.H., Attia, M.E., Keep, S., Lunton, T., Randle, J.: "Cost effective surveillance of emerging aquatic weeds using robotic aircraft" project demonstration video. http://www.acfr.usyd.edu.au/research/projects/aerospace/FundRes/Weed-Helicopter-2008.wmv. Retrieved 1 March 2009
18. Trebar, M., Steele, N.: Application of distributed SVM architectures in classifying forest data cover types. Comput. Electron. Agric. **63**(2), 119–130 (2008)
19. Cortes, C., Vapnik, V.: Support-vector networks. J. Mach. Learn. **20**(3), 273–297 (1995)
20. Burges, C.J.C.: A tutorial on support vector machines for pattern recognition. J. Data Min. Knowl. Discov. **2**(2), 121–167 (1998)
21. Vapnik, V.: The nature of statistical learning theory, 2nd edn., 314 pp. Springer-Verlag New York, Inc. ISBN-10:0387987800 (1999)
22. Chang, C.C, Lin, C.J.: LIBSVM: a library for support vector machines. http://www.csie.ntu.edu.tw/~cjlin/libsvm. Retrieved 26 Feb 2008
23. Ladd, G., Nagchaudhuri, A., Earl, T.J., Mitra, M., Bland, G.: Rectification, georeferencing, and mosaiciking of images acquired with remotely operated aerial platforms. In: Proceedings of the American Society for Photogrammetry and Remote Sensing Annual Conference ASPRS 2006, 10 pp, 1–5 May 2006
24. Mostafa, M.M.R., Schwarz, K.P.: Digital image georeferencing from a multiple camera system by GPS/INS. ISPRS J. Photogramm. Remote Sens. **56**, 1–12 (2001)
25. Göktoğan, A.H.: Gimballed multimodal sensor design for unmanned aerial vehicles. In: Proc. II Aeronautics and Space Conf. (UHUK'08), pp. 16., ISBN:978-975-561-341-3. İstanbul, Türkiye, 15–17 October 2008