Autonomous UAVs Wildlife Detection Using Thermal Imaging, Predictive Navigation and Computer Vision

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Abstract—There is an increased interest on the use of Unmanned Aerial Vehicles (UAVs) for wildlife and feral animal monitoring around the world. This paper describes a novel system which uses a predictive dynamic application that places the UAV ahead of a user, with a low cost thermal camera, a small onboard computer that identifies heat signatures of a target animal from a predetermined altitude and transmits that target's GPS coordinates. A map is generated and various data sets and graphs are displayed using a GUI designed for easy use. The paper describes the hardware and software architecture and the probabilistic model for downward facing camera for the detection of an animal. Behavioral dynamics of target movement for the design of a Kalman filter and Markov model based prediction algorithm are used to place the UAV ahead of the user. Geometrical concepts and Haversine formula are applied to the maximum likelihood case in order to make a prediction regarding a future state of the user, thus delivering a new waypoint for autonomous navigation. Results show that the system is capable of autonomously locating animals from a predetermined height and generate a map showing the location of the animals ahead of the user.

Keywords— Remote sensing, Wildlife detection, feral animals remote Piloted Aircraft Systems

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1. INTRODUCTION

The process of monitoring wildlife and feral animals is a complex, laborious and sometimes expensive task which require careful planning and execution. Remote sensors (thermal camera), advanced path planning and image processing algorithms can be placed on unmanned aerial vehicles (UAVs) to provide a low cost approaches to determine critical requirements for spatial and spectral distribution of wildlife [1-5]. Leira, et al. [6] for example discuss using thermal camera with UAV for detection objects in the ocean surface. They used on-board real time algorithm to identify and track object at the ocean surface. They achieve 99.6% accuracy of detecting objects of interest located on the ocean's surface. Also, the algorithm accuracy was 93.3% when detecting the different object types the system is trained to classify.

Han [7] discusses using thermal infrared (TIR) for use in an algorithm called random M-least square to discover the optimized projective transformation factors between TIR frames. The results have shown the recorded TIR frames can create a variety of possible real-time applications are in the future.

One of the main challenges is obtaining accurate results with the target detection algorithm while also being able to process images on the platform in real time [8-10]. To achieve this stage a variety of masks can be used, the object must fit that target animal mask to be a positive detection.

In our previous work Cooper, et al [11] describes a system that uses a probabilistic model for autonomous forward facing environmental sensing or photography of a target. The system is based on low-cost and readily-available sensor system in dynamic environments and with the general intent of improving the capabilities of dynamic waypoint-based navigation systems for a low-cost UAV. We tested a Kalman filter and Markov model-based prediction algorithm for target movement of the design. The results of the application for aerial filming with low-cost UAV are presented, achieving the desired goal of maintained front on perspective without significant constraint to the route or pace of target movement [11].

In this paper the predictive navigation work is used but is extended to use computer vision algorithms and thermal cameras to identify animals from their surroundings [11]. The system is capable of identifying heat signatures of a target animal from a predetermined altitude, determine what that target's GPS coordinates are and then wirelessly transmit those coordinates and display them on a graphical user interface (GUI) in real time [6, 12].

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The rest of this paper is organized as follows. Section 2 discusses the system architecture and the integration of the components. Section 3 discusses the image processing algorithm, target detection and estimating the location of an object system onboard the UAV. Section 4 discusses the predictive navigation algorithm. Section 5 discusses the results achieved by applying this system for animal detection. Section 6 then discusses the conclusion and future work.

2. SYSTEM DESCRIPTION

2.1 System Architecture

The system architecture is divided into two parts as shown in Figure 1. The airborne system consists of a multi-rotor UAV type (3DR IRIS), an autopilot (Pixhawk), a thermal camera (FLIR Lepton), a microcomputer (Raspberry Pi 2) and GPS (3DR brand) module on an airborne platform. The radio modem used is the Xbee pro2.

The image detection algorithm is developed and installed on-board the microcomputer (Raspberry Pi 2). The microcomputer has the FLIR Lepton camera and the GPS directly connected to it.

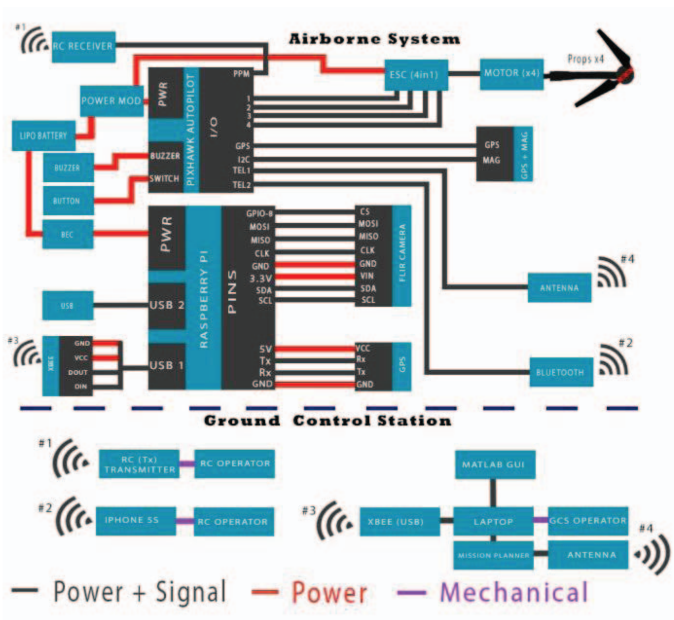

Figure 1: System Architecture [Airborne Elements & Ground station control]

The on-board computer (Raspberry Pi 2) will receive GPS coordinates from a separate GPS module to the pixhawks GPS, and then the images captured from the camera are then scanned for signs of wildlife using the detection algorithm on the microcomputer. The coordinates of the detected animal are then sent to the Ground Control Station (GCS) to be processed. The Xbees are chosen for communication because of their low power usage and adequate transfer rates to the GCS.

Figure 2 illustrates the airborne subsystems. A modified 3DR IRIS is used in this project. The frame is capable of a payload capacity of 425 grams [14, 15]. A Pixhawk autopilot is utilised in this system [16]. A Raspberry pi 2 is used as the UAV on-board microcomputer to process the detection algorithm on-board [19]. The Raspberry Pi 2 is physically connected to thermal camera, GPS and Xbee [18].

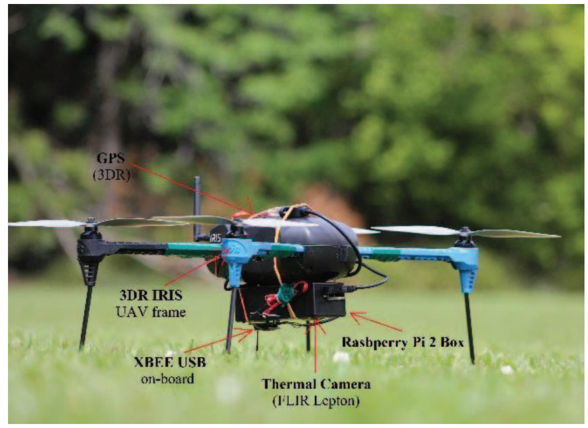

Figure 2: System design

2.2 System Integration.

The Xbee receives the GPS coordinates of the UAV. The Xbee connected to the GCS also receives the coordinates for the images which have a significant wildlife sign, showing the relative position of the animal detected to the frame in pixel value.

Figure 3 and Figure 4 illustrates the integration between the Raspberry Pi 2 and the thermal camera (FLIR Lepton). The FLIR lepton is connected to a Raspberry Pi 2 microprocessor using the breakout board. The FLIR Lepton camera module is small thermal camera which takes 60 by 80 pixel footage [18]. This camera allows the testing algorithms on a smaller airborne platform like the IRIS multirotor which has a limited payload capacity.

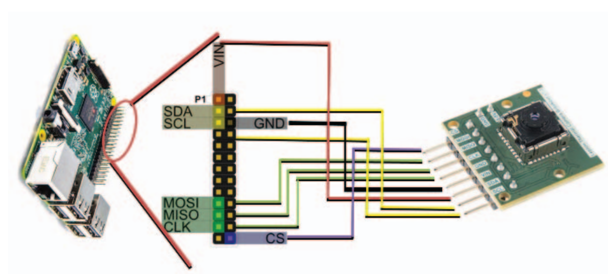

Figure 3: Diagram for Raspberry Pi 2 - FLIR Lepton Connection

The Raspberry Pi is integrated with both GPS and Xbee as shown in Fig 4. The aim of using GPS with the Raspberry Pi is to send the location of the UAV and animal to the GCS. There is also a Xbee connected to the GCS to receive the coordinates of the multirotor. The pixel location of the target animal is also sent once the images are processed on-board with the Raspberry Pi 2. The serial connection can send GPS coordinates from air to ground thus allowing the GCS to track the telemetry of the UAV and the display the location of the target. (See section 3 Image Processing System)

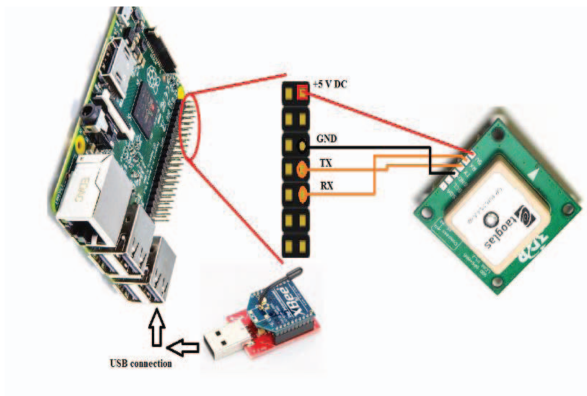

Figure 4: Integration diagram for Raspberry pi 2 with GPS and Xbee

A GUI has been developed for the GCS to receive the GPS coordinates of the UAV. When the target GPS coordinate is received, the program will display a geographical map with the target location and the UAV flight path. In addition, there are two separate options which allow the code to work online or offline in remote areas. The offline mode requires an alternate map to be downloaded and selected for use through the GUI.

3. Image Processing System

3.1 Frame Work

The algorithm is designed to automatically detect wildlife and is written using Python and a pixel based object detection algorithm [15, 16]. This algorithm makes use of the thermal camera and OpenCV, an open source computer vision library wrapped for Python. The algorithm consists of a few steps as shown in the flowchart in Figure 5.

The algorithm consists of several steps. During the first step the system uses the prediction algorithm. In step 2 the system scans the area using thermal camera takes one image every second. Then the image is loaded into a (60x80) with colour intensities representing each pixel. The image is then displayed in greyscale in the two dimensional matrix with values being between 1 and 255. The fourth step, the image is stamped with GPS coordinates in order to know the location of each image and blob detection is applied. To do this the matrix will be set a threshold which all the pixels above a certain value will be 1 and all others will be 255. The threshold is set so only the hottest objects will be shown in each image frame.

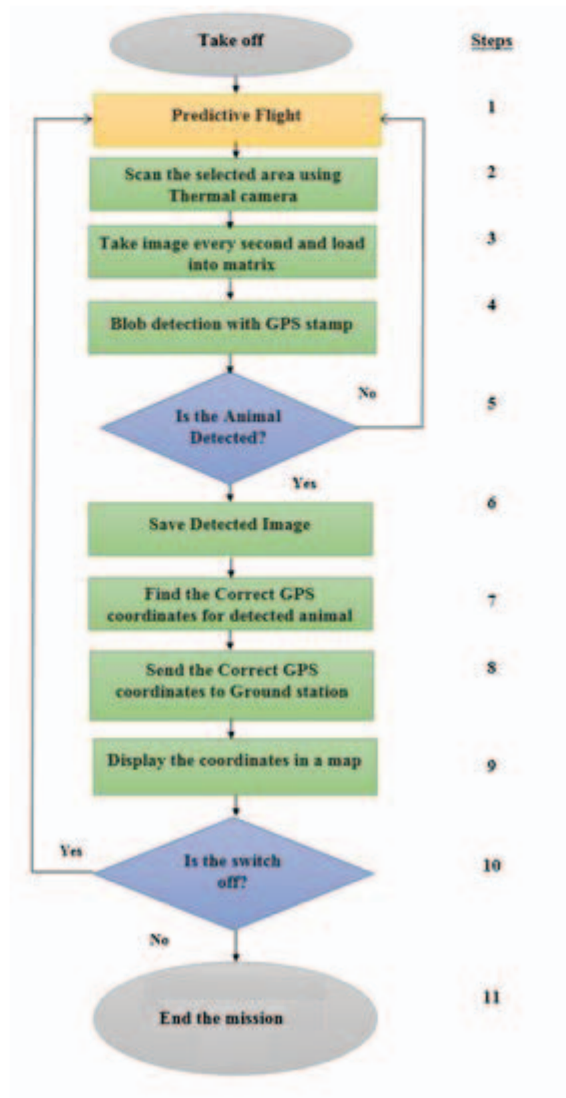

Figure 5: On-board animal's detection Flowchart

Step five is a condition that compares if the animal is detected or not. If the animal is detected, the image is saved as shown in step six else the code will go back to the first step. The code will find the correct pixel coordinates of the detection in the image and send them to the GCS. Where the GUI will then convert the location into GPS coordinates. Indicating the location of the detected animal. In step 9 the algorithm displays a map for the animal's location in the GCS. During step 10 the switch of the operation is checked to see if whether it will continue to run the algorithm. If the switch is off it will no longer take pictures and the mission will terminate.

3.2 Target Detection

The target detection algorithms (steps 4 and 5) use OpenCV and Python [14]. The method used is to micro calcify clusters according to specific features [16]. The code detects a ‘blobs’ when numerous pixels of the same value are all next to each other.

3.2 Estimating the Location of an Object

Trigonometry (Figure 6) is applied to find the correct GPS location for the animal (step 7). The camera field of view (FOV) is an angle of 22^0 is used in the calculations to estimate the distance per pixel. The image detection algorithm discussed earlier sends the pixel values back to the GCS where the GPS location is corrected.

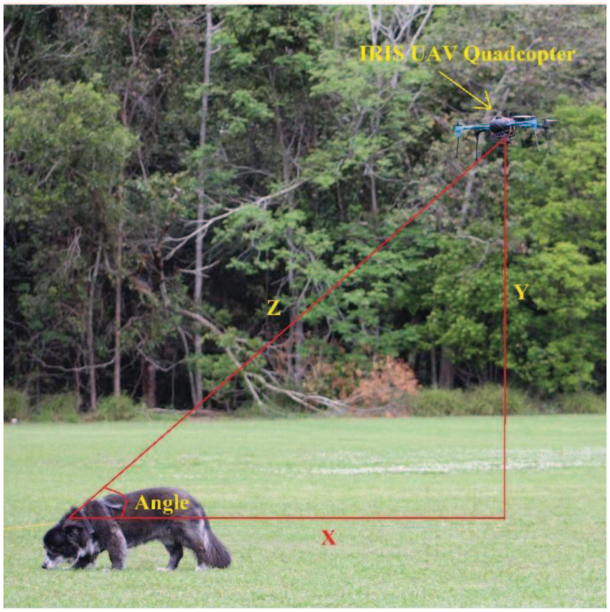

Figure 6: Pythagoras theorem applied in this system

Since the GPS location of the image frame is referenced from the center of the image, the GPS must be corrected so that animals on the edges of the frame can be located more accurately. The pixel values are given to the software in x and y Cartesian coordinates, then multiplied by the distance per pixel in their respective directions. The x and y directions are then rotated depending on the heading of the UAV using the rotation matrix:

$$Rotation\ Matrix = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

Where θ is the UAV heading. This has to be corrected as a heading value is referenced from the y-axis whereas the rotation matrix is referenced form the x-axis. Simple If statements are used to correct these so both are on the same reference frame. The heading is determined from the last two GPS coordinates and multiplied by the rotation matrix. The corrected x, y coordinates can then converted to longitude and latitude values respectively.

4. Prediction Algorithm

The predictive model (Figure 7) uses an iPhone application (Figure 8) which is connected to the Pixhawk via a Bluetooth module. The Bluetooth module is connected into the telemetry 2 port of the Pixhawk autopilot. The app itself uses a Kalman filter and a Markov model-based prediction algorithm to determine the direction of the user. Geometrical concepts such as the Haversine formula are applied to the maximum likelihood case in order to make a prediction regarding a future state of the user, thus delivering a new waypoint for autonomous navigation. Figure (8) depicts a screenshot of the applied application that is used to fly ahead of the vehicles position. The software is easy to use and easy to integrate with the IRIS multirotor. This predictive capability was integrated with our system for extra functionality.

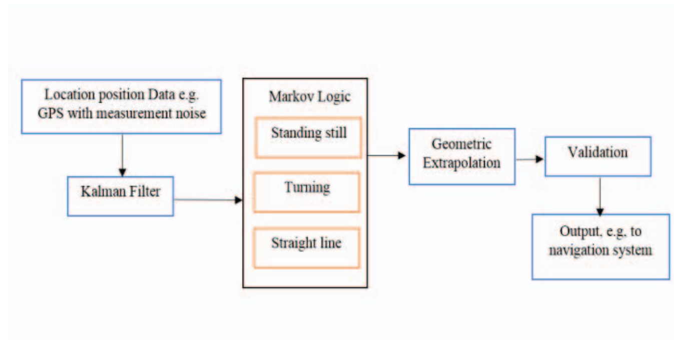

Figure 7: Block diagram of the prediction model [7]

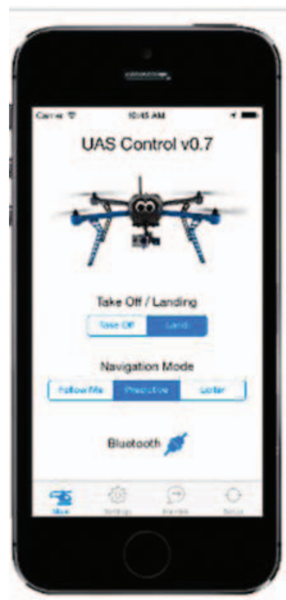

Figure 8: iPhone application.

Figure **7** depicts the block diagram of the predictive navigation model. The user’s current GPS data is downloaded into the Kalman filter to give a better representation of human movement. Markov Logic is then applied to determine if the user is turning, walking in a straight line or standing still by analysing the previous data points. Once a state is assigned to the motion of the user, a least-squares regression algorithm is implemented to extrapolate the data for a probable prediction solution. The Harversine formula is then implemented to the predicted

GPS location based on the users expected relative displacement. The data is then validated by performing a vector magnitude calculation to ensure user is following the same path so that the UAV does not stray off course. Once the data is validated it is then uploaded to the autopilots navigation system via Bluetooth.

5. Test Results

During testing, the UAV is commanded to fly at a height of 10 meters and 10 meters in front of the user. In this test the target animal is a single dog. The results are shown in the Figure 9. The figure is divided into three parts. Figure 9 (A) shows the UAV with thermal camera flight above and behind the dog. Figure 9 (B) shows the original thermal capture image by the on-board thermal camera. Figure 9 (C) shows the processes images by the Raspberry pi on-board the UAV.

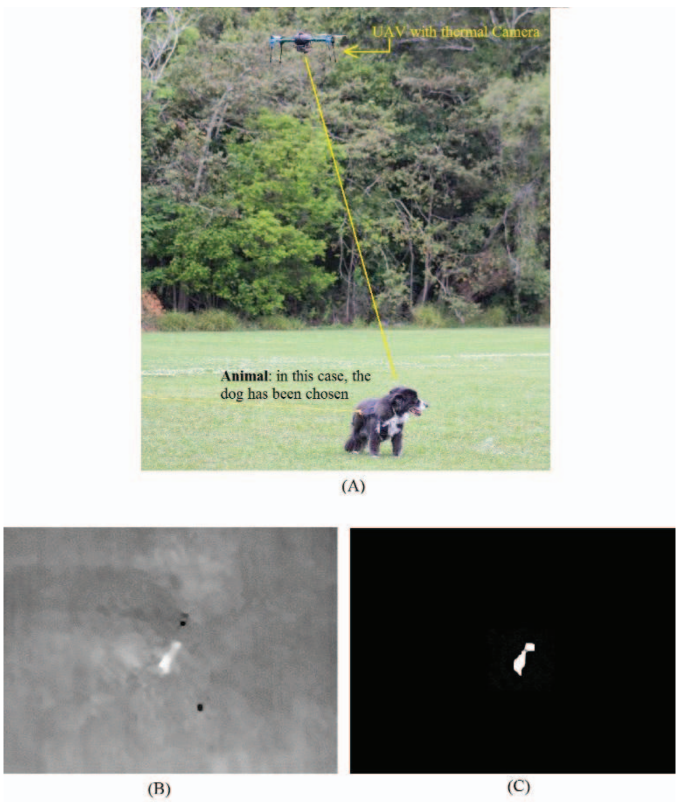

Figure 9: Animal detection, (A): UAV above and ahead of the target (B): Thermal image is taken by the UAV, (C): Thermal image after being processes by the algorithm

The dog is shown to be detected and located both of the times it flew over. Figure 10 shows both the location of the dog and the path the UAV took. The red dots represent the flight path of the UAV, the triangles represent the dog's location determined by using GPS on a mobile phone, and the blue crosses represent the predicted location of the animal using the detection algorithm.

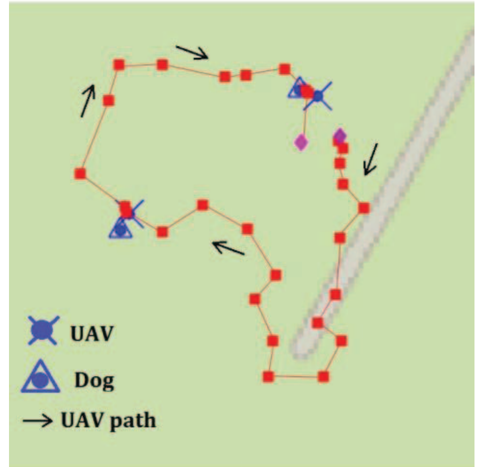

Figure 10: Flight Data showing Detection and GPS

The location of the dog in both cases is shown to be found. The accuracy of the GPS location was determined to be within 2m radius of the detection.

6. Conclusion and Future Work

This paper describes a system to autonomously detect wildlife using a low cost UAV, a prediction model, computer vision and thermal imaging. The results show that this system is an effective low cost, standalone system capable of detecting animals using thermal sensors. This system makes use of a microcomputer to run a detection algorithm using a low cost thermal sensor and GPS module. The system proved that it is possible to detect wildlife using a thermal sensor and GPS on an airborne platform, and send the detected data (images, GPS location) wirelessly to a GCS to be analyzed. The predictive iPhone application has been integrated to this system to show potential uses for the system in agricultural environments or search and rescue remote sensing. In future a higher resolution thermal camera can be utilized to improve upon the thermal imaging and make it possible to distinguish between different animals.

The algorithms are open-source. Please contact one of the authors for more information.

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BIOGRAPHY

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