Use of Unmanned Aerial Vehicles for Wildlife Monitoring

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Abstract: Recent developments in UAV (unmanned aerial vehicle) engineering have pushed the usage of the so-called "drones" into the mainstream. The omni-purpose nature of these vehicles has caused increase in customer demand across various fields. Mass production has resulted in drop in prices, especially for less sophisticated recreational vehicles. However, in order to capture quality imagery for further processing the technical sophistication of the mounted camera is the deciding factor, not the UAV itself. Many researchers are looking for options to exploit this technology in different fields, one of which is wildlife monitoring. This paper aims to present basic overview of knowledge in the area of aerial wildlife censusing and the progress made during a research conducted at Czech University of Life Sciences Prague.

Keywords: Image recognition, UAV, wildlife, drones, thermal imaging.

1 Introduction

Efforts to accurately estimate numbers of wildlife animals are around for centuries. Nowadays, these census results are the basis for determining the amount of hunting needed to ensure stable populations. In most European countries, including the Czech Republic, the population of hoofed wildlife has increased in recent decades, causing more and more damage to forest and field cultures (Bartoš et al., 2010). In order for the number estimates to help fulfill a control function, results must roughly correspond to reality. Nowadays, commonly used methods in the Czech Republic affect only 10-33% of the actual population. However, the accuracy of estimates of game conditions is eloquently evidenced by a comparison of the spring basal state with the number of animals being hunted (Kotrba et al., 2005). According to statistics from some countries, occasionally more animals were hunted than the amount of animals that should be present according to the census, which is sometimes also the case for the Czech Republic. Another common method is to use data from camera traps, but the results from such a survey can often be very unreliable (Claridge and Paull, 2014; Foster and Harmsen, 2012). That is why new alternative and more efficient methods are being sought.

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Better results can usually be achieved using a powerful technology, but its use alone does not guarantee the quality of the outputs. The first findings on aerial census have been published more than forty years ago (Graves et al., 1972). Censusing of game from an aircraft or a helicopter is practiced for example in the Scandinavian countries (Liberg et al., 2010). Thermal vision is often also used (e.g. Gill et al., 1997; Focardi et al., 2001 and others), but mostly for surface based deployment. In contrast, mainly in the US and Canada, thermal imaging is expanding not only in ground censuses, but in aerial imaging also. There are many published results of monitoring of various animal species in various environments (Wyatt et al., 1980; Bayliss and Yeomans, 1989; Wiggers and Beckerman 1993; Focardi et al., 2001; Garel et al., 2010; Fuentes et al., 2015).

The current development of drones and artificial intelligence tools for image evaluation brings a new dimension to the use of aerial counting and game monitoring methods. Unmanned vehicles are nowadays, mainly due to the massive expansion of the so-called multi-copters (multiple motor helicopters), known mainly by the term "drones". Officially, they are called by the term UAV - Unmanned Aerial Vehicle. Unmanned vehicles offer different ways of imaging by combining imagery from varying flight altitudes. This at the same time presents new options for retrieving data from selected areas in real time. Some UAVs are capable of covering an area of several square kilometers, making them a cheaper and more affordable alternative to conventional aircraft. Because of the lower scanning height, it is also possible to obtain very detailed images from an unmanned vehicle (Eisenbeiss, 2011). In addition to capturing images, monitoring can also be performed "on-the-fly" without recording, but only transmitting the video to the operator screen.

2 Data acquisition

In order to obtain imagery data for developing the most precise image processing methodology, our research team has conducted several preliminary flights. In cooperation with employees of Military Forests and Farms (state company) two enclosed areas were selected that contain a known number of animals. First area is without any significant vegetation apart from few trees around the borders (see Figure 1). It is basically a small outdoor livestock confinement area. Second chosen area is larger with few dozen trees and some bushes and more closely resembles a game reserve park.

Fig. 1: Ground photo of first testing site

2.1 Equipment

Drone DJI S900 (see Figure 2) was used to conduct the preliminary data acquisition. It was equipped with standard camera as well as thermal camera Flir Tau 2. GPS module was also installed in order to help with navigation and to provide the ability to mark obtained data with location coordinates.

Fig. 2: DJI S900 multi-copter used to obtain preliminary testing data

The drone was used in compliance with all current legislation regarding use of UAVs in Czech Republic.

2.2 Flight specifications

Before the actual data acquisition, it was necessary to determine flight height, speed and pattern to obtain best possible data for analysis. The maximum possible flight height for drones in Czech Republic is 300 meters. Such distance might however result in video recording that due to its resolution will not provide sufficient detail for the image recognition algorithms to function properly. If the flight height was set too low, it would result in better quality imagery, but it would take considerably more time to conduct such flight and cover entirety of given area. Also low flight height has higher risk of animals noticing the drone and running from it. As a compromise a flight height between 50 to 60 meters was selected.

In order to cover an entire area where the measurements will be taking place a standard “zig-zag” or “lawn mower” pattern was selected as most efficient. In case the area is not convex it is possible to divide it into smaller convex polygons. Second option is to circumscribe the area with smallest possible bigger convex area. This may result into capturing imagery of areas that is not of importance, but if the cut-out area is not very large, it might be more efficient than flying several smaller paths over several polygons. Flying in this pattern (along the longer side) will minimize the number of turns the UAV has to make.

Another issue is the selection of overlap throughout the pattern. Movement of animals is to be expected and it is possible that a herd might move from one section of given area onto another, therefore avoiding being captured by the UAV camera on both passes. Or the opposite might happen – that same animals will be captured two or more times in different sections of the flight path. Even if we assume that animals will be stationary, a certain overlap is necessary to prevent issues of animals being captured by the camera only on the edges of the screen, because image recognition algorithms generally work better if the objects being searched for are in the center area. Since the testing sites are both relatively small, we opted for high overlap during the preliminary data acquisition. For further flights we plan to adjust the actual overlap based on the extent of observed animal movement.

Lastly it is necessary to determine the camera angle. If the camera is positioned too much to the side (more horizontally than vertically), the actual distance to the ground would increase and also any obstructions like trees and terrain would have more significant impact on the imagery. If the camera is positioned fully vertically however, the captured images of animals would be fully top-to-bottom, therefore missing the animals' extremities. A picture without limbs might drastically reduce successful object classification by the image recognition algorithm as suggested by the research results by Chrétien et al., (2015). For the testing we selected a relatively high angle of depression - approximately 55 to 65 degrees.

2.3 Initial flight results

The testing flights on both chosen sites provided several crucial insights. First of all, that the sound of multi-copter engine as well as its presence above the area scared the animals into running away from it. Since it was fenced area, once the herd reached the edge the animals clumped together and stood still waiting (see Figure 3). This may affect the monitoring both positively and negatively. If the herd is approached by the UAV from unfavorable angle it may cause them to run aside therefore avoiding being captured by the camera. However if the herd runs away in the direction of the flight and is therefore "chased", it may prove incredibly useful. If that were to happen, there would be more images available providing more data for image recognition. Also in case of areas with higher vegetation this may cause the animals to significantly move, increasing the chances of capturing an image with unblocked view when chasing the animals through a clearing.

Fig. 3: Aerial photo of first testing site

The importance of getting a clear view of the animals became apparent during test flight over the second chosen testing site (see Figure 4). Even though the amount of trees is not very high (average Czech forests are much denser), they provided significant cover for the animals to hide. This along with the effect of terrain shadow (can be seen in both Figures 3 and 4), can make obtained imagery unsuitable for accurate processing.

Fig. 4: Aerial photo of second testing site

3 Data processing methods

In order to determine the best suitable methods for image processing our team has conducted the following overview of current state of the art:

Image processing of a recognized object consists of a series of steps. First, you need to capture and digitize the image, and then use the image preprocessing method to improve the image, which is especially focused on grayscale, brightness and contrast adjustment, histogram equalization, image sharpening, and various filtration methods. Another important step is to use segmentation methods to distinguish a recognized object from the background. It is primarily segmentation by thresholding, image dyeing algorithms, edge detection and linking methods and various algorithms for filling objects. The next image-processing phase is the object description. The most well known methods of object description include the momentum method, Fourier descriptors and chain codes that can also be used for so-called structural description of objects. The final stage of the image processing process is the object's classification (recognition). The task of classification is to classify objects found in the image into a group of previously known classes (Parker J.R., 2011). Custom object recognition can be accomplished using artificial intelligence or statistical analysis. Typically, the acquired description of the object will be presented to the classifier, which can determine with certain degree of accuracy, which object it is. The classifier is familiar with the objects that can be submitted to it. This process is called learning.

An example can be the SIFT (Scale-Invariant Feature Transform) method, which was first used to detect objects in the image scene. According to Noviyanto and Arymurthy (2013) for the identification of bovine animals, SIFT method achieves the best results. From the training set of images, vector object vectors are calculated, which are subsequently searched in test pictures. If the vectors obtained during training and testing were sufficiently matched, the object was detected and recognized at the same time. This principle can, however, be equally well used in classification. From the training sets (one for each class), the signifier vectors are obtained by the algorithm and are then compared with the vectors counted for the test set. In the next step, using the selected classification method, it is decided to divide the elements of the test set into individual classes.

SIFT consists of four main steps (Lowe, 1999 and Lowe, 2004):

1. detection of extremes within scale-space
2. refinement of the location of significant points
3. assigning orientation to significant points
4. compiling a descriptor of significant points

Yu et al., (2013) have published an analysis that shows that the combination of SIFT and CLBP (Compound Local Binary Pattern) can serve as a useful technique for recognizing animals in real complex situations. They use enhanced spatial pyramid matching (ScSPM), which extracts dense SIFT descriptors and mobile-structured LBP (or CLBP) as a local function that generates global functions via weighted sparse encoding and max pooling using the multi-scale kernel pyramid, and sorts images according to the linear support vector machine algorithm.

4 Conclusions

The two test flights conducted to obtain initial data for further analysis provided several key insights. Even though the UAV flies at relatively high altitude, the engine noise is still loud enough to startle or scare animals and cause significant movement of the entire herd. Images taken by a regular camera show that unless animals are captured on top an area with little to no vegetation, the imagery might be unsuitable for deployment of image recognition algorithms. Trees and larger bushes provide cover to the animals and are a significant obstruction. The effect of terrain shadow also reduces the perspicuity of captured images. Overall the test flights suggest that for monitoring in forest environments use of regular CCD camera might be insufficient.

Our research efforts will therefore shift more towards the use of thermal imaging or night vision imaging using the dynamic light spot method. Both of these techniques are more likely to provide quality data suitable to be used as an input for image recognition algorithms. As for the image recognition itself, we are planning to use the SIFT method as our first option, since it has proven as highly suitable for successfully recognizing and classifying images of wildlife hoofed animals by other researchers. The issue is that so far the SIFT method was mainly used for ground based imagery gathered by regular camera traps. Images taken from aerial view at a high depression angle may not result in accurate assessments. In case we do not succeed with this approach we will either adjust the flight specifications (flight altitude, camera angle etc.) to better suit the SIFT method or look for a different algorithm altogether.

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