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Automatic population counts for improved wildlife management using aerial photography

B. Sirmacek[a], M. Wegmann[b], A.D.P. Cross[c], J.G.C. Hopcraft[d], P. Reinartz[a] and S. Dech[a]

[a]*German Aerospace Center, Earth Observation Center, Oberpfaffenhofen, Germany (Beril.Sirmacek@dlr.de, Peter.Reinartz@dlr.de, Stefan.Dech@dlr.de)*
[b]*University of Würzburg, Department of Remote Sensing, Würzburg, Germany (martin.wegmann@uni-wuerzburg.de)*
[c]*University of Glasgow, Institute of Biodiversity, UK (a.cross.1@student.gla.ac.uk)*
[d]*Frankfurt Zoological Society, Bernhard-Grzimek-Allee, Frankfurt, Germany (granthopcraft@fzs.org)*

Abstract: For effective conservation management, it is very important to provide accurate estimates of animal populations with certain time intervals. So far many studies are performed visually/manually which requires much time and is prone to errors. Besides, only a limited area can be considered for counting because of the effort required. In order to bring a new solution to this problem, herein we propose a novel approach for counting animals from aerial images by using computer vision techniques.

To do so, we apply a probabilistic framework on local features in the image whose spectral reflectance differs from the surrounding region. We use mean shift segmentation and obtain probability density function (pdf) to detect focus of attention regions (FOA). Finally, we benefit from graph theory to detect segments which should represent animals. We test the feasibility of the proposed approach using aerial images of varying quality and angles (including orthogonal time lapse photography) from several different terrestrial ecosystems. Monitored species include birds and mammals. The algorithms successfully detect and count animals and provide a replicable and objective method for estimating animal abundance, however the methodology still requires estimates of error to be incorporated. This approach highlights how technical innovations in remote sensing can provide valuable information for conservation management.

***Keywords**:* Aerial imagery, Local Feature Extraction, Probability Density Function, Mean-Shift Segmentation, Graph Theory, Graph-Cut, Animal Detection, Animal Counting.

1 INTRODUCTION

Effective conservation management relies on accurate estimates of animal abundance. Many censuses use field survey techniques that manually enumerate the number of individuals from aerial photography. These approaches are very time-consuming and limit the number of censuses that can be conducted in an area. Hence an automatic animal detection and counting method would greatly assist conservation management. By providing fast and consistent information about animal abundance, insights into the causal relationships that determine animal distribution and population dynamics can be rapidly ascertained, especially with respect to land-use change. Moreover, the applicability of space-borne remote sensing data which could be used in future can be evaluated against data from aerial photography.

In related literature, one of the earliest scientific analyses is made by Norton-Griffiths [1973] by discussing possibilities of collecting accurate animal counts from aerial images. Laliberte and Ripple [2003] used an image analysis program to count objects representing animals in aerial images. Groom et al. [2011] used an image segmentation based method to count flamingos from remotely sensed images. Descamps et al. [2011] proposed a computer vision approach based on application of birth-and-death algorithm on aerial images in order to detect and count large birds. Raybould et al. [2000], proposed an image processing approach to estimate number of people in outdoor events from aerial images. Lonergan et al. [2011] used aerial and satellite images to obtain seasonal and yearly count patterns of British grey seals. Thomas [1996], used aerial images to count yearly patterns of caribous. McNeil et al. [2011] used a classification based method to segment background and foreground objects in aerial images to count penguins. Jachmann [2002] compared the accuracy of aerial counts with ground counts and discussed the effect of animal sizes, flight and weather conditions on aerial counting performances. In addition, Tratham [2004] used a further analytical technique to count macaroni penguins from color aerial photography. The results showed a strong correlation between the estimates of automated image analysis and manual ground counts.

Sirmacek and Reinartz used aerial images to bring automated solutions to person detection and counting problem. In their initial study [2011b], they proposed a dense crowd detection method based on extraction of local features from airborne images. Local features are used in a probabilistic process to identify locations of dense crowds. In a following study [2011c], they improved the dense crowd detection study by adding a feature selection step. By using a background comparison method, they detected individuals. They applied Kalman filtering on individual detection results (which are obtained over registered airborne image sequences) to obtain automatic tracking results. Using several measures they have extracted over automatically generated probability density functions, they also estimated the main direction of motion and abnormality level of large crowds [2011a]. Burkert et al. [2011], used their estimations in order to simulate the human activity in large areas. All these studied show that, aerial images can be used to monitor human activities, to detect and track individuals. Availability of high resolution sensor data, and the software system developments in human monitoring field lead us to develop algorithms further in order to monitor and count animals from these images in order to help effective conservation management.

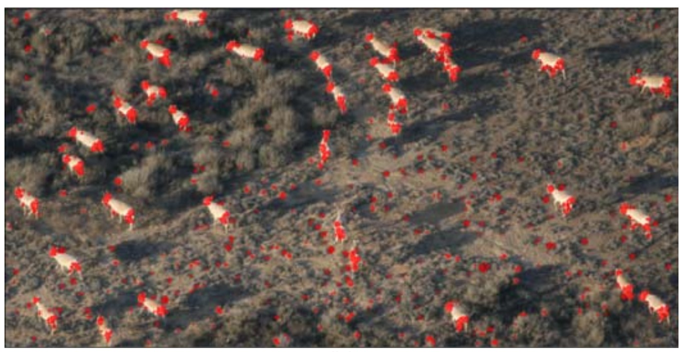
Here we propose a novel system which is based on applying image processing and computer vision techniques to aerial photography in order to automate the detection, identification, and enumeration of animals. Our approach depends on local feature extraction from input aerial images. Extracted features are used as observation points to generate a probability density function (pdf). Using pdf and segmentation result of the input image we detect focus of attention regions (FOA) which help us to simplify our animal detection problem. Inside of FOA regions, we apply a graph theory based on the animal detection algorithm and to finally obtain the number of animals in the input image. The results from our aerial images which are from various test environments show that remote sensing and computer vision approaches can be a valuable information source for animal conservation management. In the following section we start with introducing local feature extraction from input aerial images.

2 LOCAL FEATURE EXTRACTION

For local feature extraction, we use features from accelerated segment test (FAST). FAST feature extraction method is especially developed for corner detection purposes by Rosten et al. [2010], however it also gives responses on small regions which are significantly different than its surrounding pixels. Sirmacek and Unsalan experimented to use this feature extraction method for detecting object characteristics in satellite images [2011]. Their test results prove that FAST features can be used to extract important interest locations in remotely sensed images.

In this study, we use the intensity band of the input image for FAST feature extraction. We assume (x_i, y_i) $i \in [1, 2, \ldots, K_i]$ as extracted FAST local features. Here, the Ki indicate the maximum number of features. In Figure 1 (a) and (b), we represent our $Test_1$ image from our database and the extracted local features respectively. In the next step we use extracted local features to estimate pdf.

(a)



(b)

Figure 1. (a) Original $Test_1$ aerial image, (b) extracted FAST features

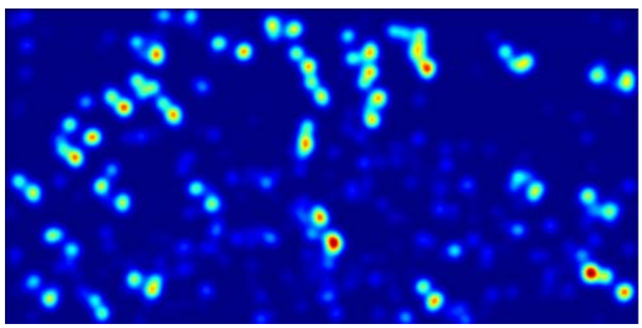
3 PROBABILITY DENSITY ANALYSIS

Since we have no pre-information about animal locations in the image, we formulate the animal detection method using a probabilistic framework. We assume each FAST feature as an observation of a probability density function to be estimated. For the locations where an animal exists, we assume that more local features should come together. Therefore, knowing the pdf will lead to detection of animal locations. For pdf estimation, we benefit from a kernel based density estimation method. Using Gaussian symmetric kernel functions, the pdf is formed as below;

$$p(x,y) = \frac{1}{R}\sum_{i=1}^{K_i}\frac{1}{\sqrt{2\pi\sigma}}exp(-\frac{(x-x_i)^2+(y-y_i)^2}{2\sigma})$$

(1)

where σ is the bandwidth (smoothing parameter) of the Gaussian kernel, and R is the normalizing constant to normalize $p(x,y)$ values between [0,1]. In kernel based density estimation the main problem is how to choose the bandwidth of the Gaussian kernel, since the estimated pdf directly depends on this value. For instance, if the resolution of the camera increases or if the altitude of the plane decreases, the pixel distance between two local features will increase. That means, Gaussian kernels with larger bandwidths will make these two features connected and will lead to detect them as a group. Therefore, the bandwidth of the Gaussian kernel should be adapted for any given input image. In probability theory, there are several methods to estimate the bandwidth of kernel functions for given observations such as statistical classification based methods, and balloon estimators. Unfortunately, those approaches require very high computation time especially when many observation points exist. For time efficiency, we follow an approach which is slightly different from balloon estimators. First, we pick $K_i/2$ number of random observations to reduce the computation time. For each observation location, we compute the distance to the nearest neighbour observation point. Then, the mean of all distances gives us a number l. We assume that the variance of the Gaussian kernel (σ^2) should be equal or greater than l. In order to guarantee the intersection of kernels of two close observations, we assume the variance of Gaussian kernel as $5l$ in our study. If there is an aerial image sequence, this value is computed only for one time over one image. Then, the same σ value is used for all images of the same sequence. Our automatic kernel bandwidth estimation method makes the algorithm robust to scale and resolution changes. In Figure 2 (a), we represent the pdf detected with extracted FAST local features.



(a)

(b)

Figure 2. (a) Obtained pdf for $Test_1$ aerial image, (b) extracted FOA regions

4 DETECTING FOCUS OF ATTENTION (FOA)

After calculating $p(x,y)$, we use Otsu's automatic thresholding method on this pdf to detect regions having high probability values which indicates focus of attention (FOA) regions. This FOA is stored in a binary image $B(x,y)$ [Otsu, 2009]. After thresholding, depending on the resolution of the input data, binary regions smaller than X pixels are eliminated since they cannot indicate FOA regions suitable for animals. In Figure 2 (b), we represent detected FOA regions (in this case X=1000) for $Test_1$ image.

5 DETECTING ANIMALS BASED ON SEGMENTATION AND GRAPH THEORY

We apply segmentation to FOA regions in order to detect locations of animals inside those regions. For segmentation, we benefit from the mean shift segmentation approach which was proposed by Comanicu and Meer [2002]. Within the mean shift segmentation process, we choose the spatial bandwidth (h_s) and the spectral bandwidth (h_r) parameters as 7 and 6.5 respectively after extensive tests, and we use the same parameters for all input images. The segmentation result is a new image called $S(x,y)$ which holds each segment labelled by a single color. We represent the mean shift segmentation result for our $Test_1$ image in Figure 3 (a). As can be seen in this result, mean shift segmentation reduces the complexity of the problem however the segments still do not indicate animal locations directly. Therefore, we continue our further analysis by using graph theory.

A graph G is formed as $G = (N, E)$, where N holds the nodes of this graph, and E is the edge matrix showing the relations between these nodes. In our study, N holds the mass centers of the segments which are detected by mean shift segmentation algorithm. To reconstruct graph edges, we benefit from Delaunay triangulation, since only neighbouring segments can correspond to parts of an animal. Using Delaunay triangulation, we connect only neighbouring segments which also reduce the graph complexity. Therefore, E is a $M \times M$ matrix, where M represents the total number of segments in $S(x,y)$ matrix. E is defined as $E(i,j)=1$ where $i, j \in [1, 2, 3, \ldots, M]$, if i and j nodes are connected by Delaunay triangulation. Otherwise, $E(i,j) = 0$ which means there is no edge between ith and jth nodes. Besides, we also assign a weight value to each graph edge. For ith and jth graph nodes if $E(i,j) = 1$, we assign the weight to this graph edge as w_{ij}. Here w_{ij} is the color distance between two segments, which is computed by using Euclidean distances of RGB components of ith and jth segments. The constructed graph for $Test_1$ image is represented in Figure 3 (b).

Finally, we apply graph cut to the constructed graph to obtain animal segments. We cut some graph edges of G by considering edge weights. From G, we obtain new sub-graphs as $G^s = (N^s, E^s)$, where E^s is defines as below;

$$E^s(i,j) = \begin{cases} 1 & \text{if } (E(i,j) = 1) \wedge (w_{ij} < \epsilon_1) \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

Here, ϵ_1 is the color distance threshold to decide to cut a graph edge. To calculate ϵ_1 threshold value we list histogram of all w_{ij} distances and apply Otsu's thresholding. We assume the threshold value obtained by Otsu's thresholding method as ϵ_1 threshold value to cut graph edges. After applying graph cut, we assume connected segments which are represented with G_s sub-graphs as detected animals. In Figure 3 (c), we represent detected animals in $Test_1$ aerial image.

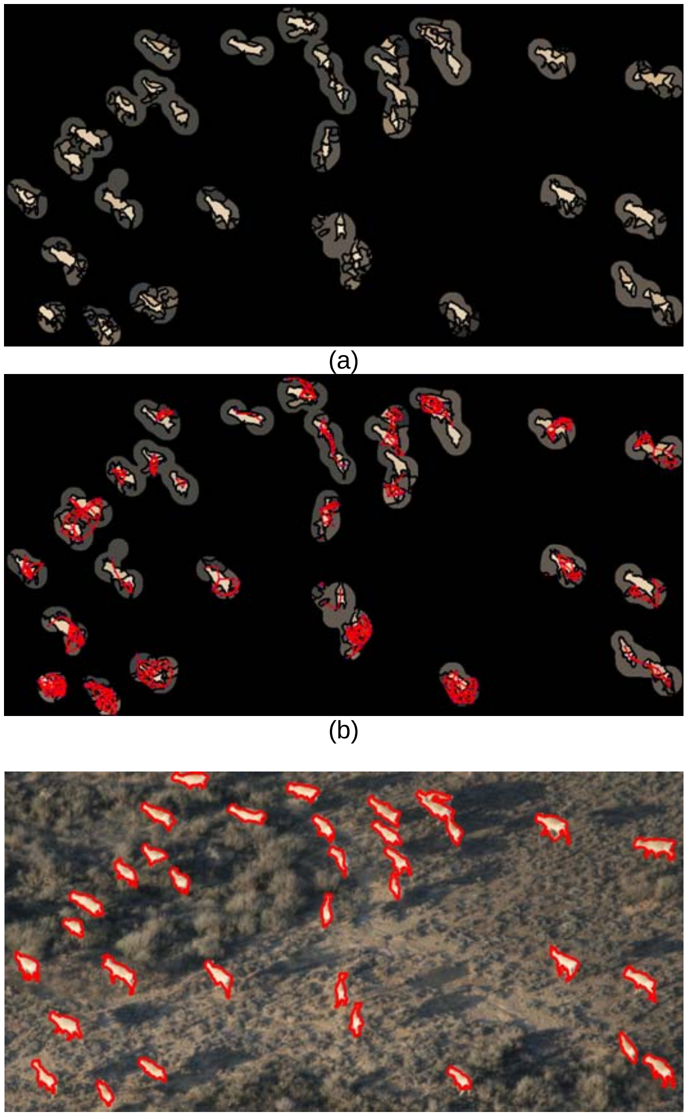


Figure 3. (a) Mean shift segments in FOA (b) Obtained subgraphs (c) Detected animals

6 EXPERIMENTS

We tested the proposed animal detection algorithm on 70 different aerial images having different animal species. We provide some of the experimental results in Figure 4. True detection and false alarm numbers are obtained as 306 and 131 respectively in 340 total numbers of animals. That corresponds to 90% true detection and 38.52% false alarm performances respectively.

(a)

(b)

Figure 4. In (a) and (b) we provide sample animal detection results for two different aerial images from our dataset.

7 CONCLUSION

Herein we propose a novel approach which is based on applying image processing and computer vision techniques to aerial photography in order to automatically detect and count animals. The proposed approach depends on local feature extraction, probabilistic detection of focus of attention regions, and graph theory based identification of animal regions. Obtained test results on our aerial images from various test environments show promising results and prove that remote sensing and computer vision approaches can be a valuable information source for animal conservation management. In the future studies, we would like to benefit from hyperspectral and termal images in order to improve results in the regions where the animals have similar colors to the earth texture. If higher resolution images are available, we also would like to focus on detecting animal species from aerial images.

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