Ecological Complexity 7 (2010) 69–75

Contents lists available at ScienceDirect

Ecological Complexity

journal homepage: www.elsevier.com/locate/ecocom

Dense and sparse aggregations in complex motion: Video coupled with simulation modeling

Thomas G. Hallam[a,*], Aruna Raghavan[a,b,1], Haritha Kolli[a,b,2], Dobromir T. Dimitrov[a,3], Paula Federico[a,4], Hairong Qi[b], Gary F. McCracken[a], Margrit Betke[c], John K. Westbrook[d], Kimberly Kennard[a], Thomas H. Kunz[e]

[a] Department of Ecology and Evolutionary Biology, University of Tennessee, Knoxville, TN 37996, USA
[b] Department of Electrical Engineering and Computer Science, University of Tennessee, Knoxville, TN 37996, USA
[c] Department of Computer Science, Boston University, Boston, MA 02215, USA
[d] USDA-ARS, Areawide Pest Management Research Unit, 2771 F&B Road, College Station, TX 77845-4966, USA
[e] Center for Ecology and Conservation Biology, Department of Biology, Boston University, 5 Cummington Street, Boston, MA 02215, USA

ARTICLE INFO

Article history:
Received 10 April 2009
Accepted 19 May 2009
Available online 28 June 2009

Keywords:
Individual-based models
Rule-based models
Ecological censusing
Brazilian free-tailed bats (*Tadarida brasiliensis*)
Noctuid moths

ABSTRACT

Investigations into the complex behaviors of aggregations of highly mobile animals have not used the link between image processing technology and simulation modeling fruitfully to address many fundamental ecological issues. Examples include population censusing, which remains difficult despite the demonstrated ecological importance of assessing abundance and density of organisms. We introduce a theoretical framework that connects thermal infrared video imaging with an individual-based simulation model—an approach that appears to be applicable to a diverse set of aggregated, highly mobile, nocturnal animals. To demonstrate the framework two applications are presented. The first is a dense aggregation of Brazilian free-tailed bats (*Tadarida brasiliensis*) that exhibits an emergence pattern that has complex dynamics and the second is a sparse local aggregation of agricultural pest moths whose dynamics are insipid. The first application uses individual-based modeling to mimic the behavior in the video of bats during a nightly emergence from a cave and to provide reliable estimates of the numbers, and associated error bounds. The second application uses video recordings of sparse aggregations to provide consistent estimates of the numbers of flying noctuid moths recorded over a corn and cotton-dominated agroecosystem in south-central Texas. This does not use a mathematical model because error estimates tend to be small.

1. Introduction

1.1. Background information for data

Various taxa ranging from moths (*Helicoverpa zea*—Westbrook et al., 1997; Wolf et al., 1986), to desert locust (*Schistocerca gregaria*; Baron, 1972; Rainey, 1989) and to bats (Davis et al., 1962; Cockrum, 1969; McCracken, 2003; Russell and McCracken, 2006) engage in spectacular flights over great distances. These flights can involve aggregations of hundreds of thousands, to even billions of individuals. For example, swarms of desert locusts have been estimated at 10 billion individuals (Sanchez-Arroyo, 2005) and similarly, flocks of the extinct passenger pigeon (*Ectopistes migratorius*) were estimated in the billions (Sullivan, 2004; Schorger, 1955). Given the magnitude of the numbers and the methods available at the time, estimates should be viewed with caution. Vigilance also extends to the antipodal end of this spectrum where censuses for small numbers of organisms such as those made for rare and endangered species (Thompson, 2004).

---

[*] Corresponding author at: Department of Ecology and Evolutionary Biology, University of Tennessee, 569 Dabney Hall, Knoxville, TN 37996, USA. Tel.: +1 865 974 4293; fax: +1 865 974 6042.

E-mail addresses: thallam@utk.edu (T.G. Hallam), Raghavan.Aruna@mayo.edu (A. Raghavan), haritha.kolli@gmail.com (H. Kolli), ddimitro@scharp.org (D.T. Dimitrov), pfederic@utk.edu (P. Federico), hqi@utk.edu (H. Qi), gmccrack@utk.edu (G.F. McCracken), betke@bu.edu (M. Betke), John.Westbrook@ars.usda.gov (J.K. Westbrook), kkennard@utk.edu (K. Kennard), kunz@bu.edu (T.H. Kunz).

[1] Current address: Mayo Clinic, Rochester, MN, USA.

[2] Current address: Excellence in Motivation, 6N Main St, Dayton, OH 45402, USA.

[3] Current address: Fred Hutchinson Cancer Research Center, P.O. Box 19024, Seattle, WA 98109-1024, USA.

[4] Current address: Mathematical Biosciences Institute The Ohio State University 1735 Neil Avenue 379 Jennings Hall Columbus, OH 43210, USA.

1476-945X/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.ecocom.2009.05.012

Fig. 1. Thermal infrared image of an emergence at Frio Cave, Uvalde, TX. In this field of view, bats are flying from right to left. The double-column exodus, caused by the geometry of the opening of the cave, is merging into a single column on the left.

During summer months, south-central Texas becomes the home of some of the largest aggregations of mammals known to mankind, both in total numbers and in population density. For example, the colony of Brazilian free-tailed bats at Frio Cave, near Uvalde, TX, has recently been estimated to contain more than 1 million individuals (Betke et al., 2008). Maternity colonies of Brazilian free-tailed bats emerge nightly from caves and bridges in massive, spectacular assemblages that can continue for several hours. Spatial-temporal patterns of emergence can be complex, ranging from apparently random dispersal to more organized formations. The most common emergence formation is that of a single undulating, serpentine-like column. Fig. 1 provides a snapshot of an emergence from Frio Cave, which has two major exits. This emergence configuration initially is that of a double column that eventually merges into a single column. The thermal infrared video, recorded at Frio Cave in summer 2000, shows column configuration and the complex emergence dynamics of the bats emerging over a period of approximately 6 s (see online materials: Video Betke_BW_filtered_Frio.mpeg).

Brazilian free-tailed bats are active in the Winter Garden area, an 8 county region of south-central Texas, largely because of an abundance of prey, many of which are agricultural pest moths (Kunz et al., 1995; Lee and McCracken, 2002; Cleveland et al., 2006). The prey of *T. brasiliensis* includes adults of several Lepidopteron species in the family Noctuidae (Whitaker et al., 1996; Lee and McCracken, 2002, 2005), whose larvae are known agricultural pests, such as fall armyworm (*Spodoptera frugiperda*), cabbage looper (*Trichoplusia ni*), tobacco budworm (*Heliothis virescens*) and corn earworm (*Helicoverpa zea*), also known as the cotton bollworm. A 15-s video segment of a moth survey is presented in the online materials (Kennard_WG_moth.video).

1.2. The modeling background

Brazilian free-tailed bats are aerial predators of nocturnal insects; both predator and prey are known to engage in related seasonal, long distance migrations (Davis et al., 1962; Westbrook et al., 1997). The bat–moth interactions in cotton agricultural systems have recently been modeled using two different approaches. The first approach uses a model based on a system of stochastic difference equations to access economic impact of bats on agroecosystems (Federico et al., 2008). The second is a rule-based approach, which is an extension of the rule-based population model for an emergence of bats, BATOIDS (Hallam et al., 2006). The latter approach uses a BATOID-INSECTOID model based upon an energetics model of bats (Hallam et al., unpublished manuscript). Both methods require census data of moth aggregations and bat colonies as inputs.

1.3. Objectives

The objectives of this paper are to indicate a theoretical framework grounded in modeling that allows application to important problems related to ecological complexity. This framework is utilized to present and develop a methodology to estimate numbers of bats and moths based on video recordings and to provide error estimates for numbers of these organisms as they disperse or forage in airborne aggregations. The novelty of this research is the construction of a mathematical model that mimics the complex behavioral dynamics of individuals in an aggregation, to use this model to develop a video of the simulated dynamics and to generate estimates of error.

We illustrate the simulation model framework with examples where the data are presented in video. The first example depicts a dense aggregation and employs a thermal infrared video of an emergence of Brazilian free-tailed bats (*Tadarida brasiliensis*) from a cave located in south-central Texas. The second represents a sparse aggregation and uses a reflectance infrared video of noctuid moths in a corn field in south-central Texas. The illustrations are based on different methodologies because they differ in scope, perspective and, to some extent, in scale.

2. Methods

2.1. A dense aggregation that exhibits complex dynamic behavior

The method for assessing a dense aggregation that exhibits complex dynamic behavior consists of four main steps: (1) develop a rule-based individual-based mathematical model that depicts flight behavior; (2) create a video from the simulation that has similar flight characteristics to those observed in the thermal infrared video; (3) employ a counting algorithm that yields error estimates that can be corroborated by the simulation video; and (4) apply the counting algorithm to enumerate and infer error estimates for the number of individuals in the censusing video. The novel issues here are the construction of the model and to find the error estimates.

2.2. Video processing

The video of a bat emergence from Frio Cave was processed using a Bayesian method described by Betke et al. (2008). Objects shown as white dots were considered bats identified by using temporal and spatial analysis of thermal intensity values. Temporal analysis involved building a model of mean and standard deviation of intensity values measured at each pixel over time. A current pixel value that differed considerably from the mean value measured at that pixel indicated that a bat may have appeared at that pixel. The method then examined the likelihood that bats were detected by additional spatial analysis of high-intensity regions in each video frame in which significant unidirectional motion was detected. These regions represented the warm bats and the relatively warm vegetation. To avoid false detections of bats where vegetation was present, the method also analyzed the intensity profile of the entire field of view. The profiles that included vegetation were relatively flat, whereas regions of pixels formed by bats contained high-intensity peaks that corresponded to the warm thorax of the bats and lower intensity values of their wings. Because the three-dimensional scene is projected onto the 2D image frame, occlusion may occur and more than one bat may be imaged in the same high-intensity region. The method by Betke et al. (2008) used the locations of the peak intensity values in a candidate region to represent the locations of single bats (white dots).

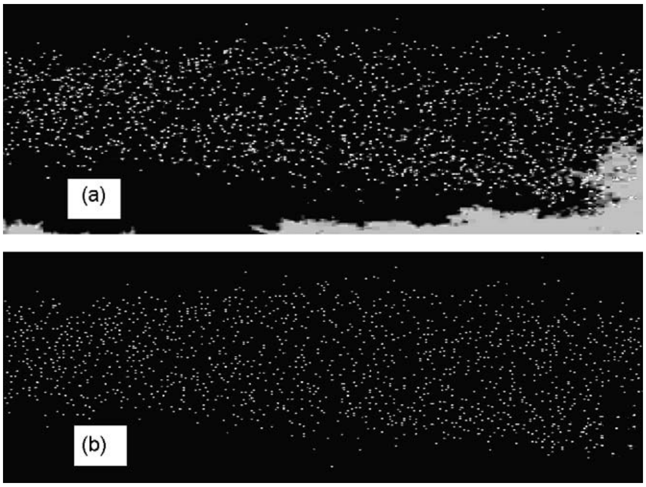

Fig. 2. Bats fly in a single-column formation from right to left across the field of view. (a) Thermal infrared video image with bats marked by white dots. (b) The same frame after removing all pixels that are not contained in high-intensity image regions.

Herein, we propose an additional detection algorithm that further analyzes the size of each region in which the method by Betke et al. (2008) deemed to have designated a bat. We assume that a region that is equal or smaller than the average-sized region in the image frame contains a single bat. We compare the size of each region to this mean (or median) size. If the size of the current region is larger than the mean (or median) size, then the ratio between the size of current region and the mean (or median) is computed and the next integer greater than this ratio is taken to be the number of bats represented by the current region. Based on our detection algorithm, we distinguish three counting methods to compute the number of individual bats in a video frame. The "without area" method ignores the size of each high-intensity region and assumes that the observed region represents only one bat. The "with mean area" method is an attempt to account for occlusion. It estimates the number of bats in a region that is larger than the mean area by the ratio between its area and the mean area. The "with median area" accounts for occlusion similarly, but uses the median instead of the mean.

The grayscale 1-byte-per-pixel representation of a frame of the thermal infrared video of the emergence at Frio Cave with the detected bats labeled as white dots is shown in Fig. 2(a). Fig. 2(b) shows the same frame in binary format with high-intensity regions representing bats in white and the background in black (i.e., with the vegetation removed).

The final step in our estimation process is to count the number of bats present in the complete video. The frames of the video were isolated and each was pre-processed. The procedure used to count the bats in the video must account for the fact that the same bat can appear in multiple frames. To eliminate multiple counting of the same bat, we computed the number of bats leaving the frames (see Fig. 3). We computed the number of departing bats by applying our counting algorithm to the edge of the image frame (region O in Fig. 3; O is chosen sufficiently small so that the transition of a bat across and exiting O has a high probability to occur from one frame to another). By summing the departing bats for all the frames and the number of bats present in the last frame, the total number of bats recorded in the video can then be estimated.

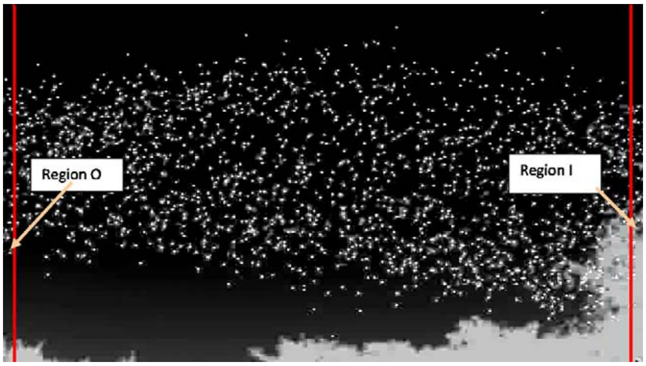

Fig. 3. Bats enter the frame on the right (region I). Our method counts the bats leaving the frame on the left (region O). The width of the regions is 1/72 of the width of the frame.

2.3. Construction of the BATOIDS simulation model

We developed a simulated model of individual bats in flight, BATOIDS, which is a rule-based individual-based formulation with rudimentary similarities to the "boids code" developed by Reynolds (1987) and is supported with a real-computational time 3D graphics package (Robert Platt, unpublished). This BATOIDS model is described in more detail in Hallam et al. (2006). Rules are specified for Velocity Matching, Collision Avoidance, Community Predator Avoidance, Individual Predator Avoidance, Subflocking, and Foraging. Three primary rules (Velocity Matching, Collision Avoidance, and Individual Predator Avoidance) govern the flight dynamics of batoids and generate spatial-dynamic patterns that are topologically similar to those observed in nightly emergences of Brazilian free-tailed bats. First, the flight velocity of each individual in the column of batoids is approximately matched to that of nearby individuals. This is accomplished by each batoid being assigned a velocity equal to the average speed in the video plus a small random perturbation rate so that the batoids have comparable averages but distinctive individual velocities. The parameters used in the BATOIDS simulator were derived from the time taken for each bat to cross a frame of the 2D video (approximately 2 s), the total time of the bat flight (approximately 6 s) and the velocity of each bat (converted pixel velocity, which is 1200 pixels/s according to the GUI of the simulation). Second, Collision Avoidance requires that each batoid maintain a minimal distance between its nearest neighbors; this property is likely implemented by bats during nightly emergences of live bats using echolocation and sight. Collisions do occur on an accidental risk level with this second rule imposed owing to their velocity and individual decisions. Third, each batoid has a tendency to minimize time spent on the boundary of the emergence column based on the assumption that bats attempt to diminish direct exposure to avian predators during nightly emergence flights (Individual Predator Avoidance). These primary rules are coupled with secondary rules to yield a transport dynamic with characteristics analogous in appearance to the dynamics of an actual emergence. Model features include column formation, a directed advective movement and complex fluctuations within the column. A snapshot of the simulation model output is given in Fig. 4. Videos of the dynamics of the simulation can be found in the online materials. The videos of the simulation include side and top views of the dynamics of the virtual emergence flight of bats. The online video

Fig. 4. A snapshot of model batoids "flying" across the landscape screen from right to left. View perspective is from the side.

Hallam_3D_emergence.wvm illustrates some of the complex dynamics that can arise in these emergence simulation videos. Also in the online materials, we have included pseudocodes (Online Figs. 3 and 4) for Community and Individual Predator Avoidance to indicate the perspective of the numerics of the simulation model.

Images taken from a video generated by the BATOIDS simulator were used to evaluate the performance of the proposed counting algorithm. Because the number of bat objects is known in the simulator, it is used as a baseline to compare with the number of objects enumerated by the counting algorithm. This estimation process provides for generation of error rates that are then translated into error estimation for the thermal infrared video.

2.4. A locally sparse aggregation

The basic census method for assessing a sparse aggregation could be similar to that above. However, unless there are significant reasons to develop error estimates for sparse aggregates, such as might be required to provide precise abundance counts for rare or endangered species, the development of a rule-based mathematical model that depicts flight behavior can be avoided or minimized. Here we focus on counting of sparse objects in a video that involves small numbers, which leads to error bounds that are small although the percentage estimates may be large. Our moth assessment application does not use a simulation model due to its sparseness but directly employs a counting algorithm to infer the number of individuals in the censusing video.

2.5. Methodology for moths

The processing methodology for the second example differs from that used in example 1 and provides a contrast between the methodology of Betke et al. (2008) and more classical approaches to counting flying organisms. A primary difference lies in the large numbers of bats versus the small numbers of moths. This example is also of interest from the need to estimate the abundance of resources for insectivores.

The highest intensity of the moths observed in the recorded video segments was 40 and the background intensity was 10. It is difficult to detect the moths from the background owing to the small differences in intensities. To solve this problem automatically, the counting was performed using image segmentation, which allows distinguishing the required object from the background objects. The classical counting approach involves image segmentation coupled with a counting mechanism (Mehmet Sezgin, 2004; Rosenfeld and Pfaltz, 1996). The most relevant of the image segmentation algorithms for our problem are thresholding and connected components labeling. These algorithms are derived by partitioning an image into regions that are similar according to a set of pre-defined criteria.

To facilitate efficient counting of moths in the video, the frames in which moths were present were computationally extracted and saved in a local directory as bitmap images. The two-step algorithm to determine the presence of a moth in the frame consists of filtering the relevant foreground pixels in each frame and labeling them using thresholding and connected component analysis. In the connected component analysis, region-growing is used first to differentiate between the background and the foreground. Once each group is determined, all pixels are labeled with a grayscale or a color (color labeling). The classical labeling approach (Rosenfeld and Pfaltz, 1996) performs two raster scans of the image. The final binary image obtained is given as the input to the connected component analysis algorithm.

Thresholding segments an image by setting all pixels whose intensity values are above a prescribed quantity to a foreground value and all the remaining pixels to a background value. Two thresholding techniques have been used—relative thresholding and automatic thresholding. The threshold value in relative thresholding was determined using a histogram. The histogram of the image indicates that pixels correspond to a moth range from intensity levels 15–40 depending on the distance of the moth from the cameras. Using relative-threshold methods, a pixel is deemed to belong to the foreground if the difference between its intensity value and the mean intensity value of the image exceeds a certain threshold. Online Figs. 1 and 2 are the histograms of a frame with a moth and one without a moth. In relative thresholding, if pixel intensity is greater than average pixel intensity by 10, they are considered foreground pixels otherwise they are regarded as background pixels.

To determine the threshold automatically, an iterative optimal threshold selective algorithm has been used. The automated-threshold method iteratively computes an optimal threshold (Qi, 1999). The minimum value of the histogram of the image was taken to be the threshold value for the program. This threshold value is used to convert the original image to a binary image. The next step in the thresholding process is curve fitting and approximation of polynomials. The threshold point is found using this method and then the counting algorithm applied to this threshold image to obtain the moth count value.

We tested two thresholds to see if a pixel is deemed to belong to the foreground: 5 and 10 grayscale levels (the dynamic range per pixel was 255 grayscale levels, i.e., 1 byte/pixel). If the difference between its intensity value and the mean intensity value of the image exceeds a certain threshold a pixel is in the foreground. If the number of foreground pixels is >2 and <300, the image is saved; otherwise, it is assumed that moths are not present and the current image can be discarded. The steps are repeated for each frame in the video. A minimum value of 2 was chosen because there were 2 bright stars in the video whose intensity was close to that of the moth and 300 was chosen as the maximum value because there were some frames which had relatively bright backgrounds due to ambient disturbances (such as increased reflectivity caused by wind moving plant leaves).

The moth-counting algorithm was developed in C#.Net. The inputs required are the path of the video file and the frame rate (in number of frames per second) at which the video was recorded. To track the progress of the video, the current frame which is being analyzed and the total frames in the video are displayed. Because the frames in which moths appear are saved during video censusing, often we can establish a "ground truth estimate" of the number of moths in the video by manually stepping through the frames that are relevant (rather than the complete video).

3. Results

3.1. Bat counting algorithms

We compared the three counting methods defined above (designated as without area, with mean area, and with median area) to compute the number of individual bats in a single frame in various batoid simulations (Online Table 1). The error bounds for the batoids simulations are used to analyze the bat census data from the thermal video. Our initial approximation of the number of bats in the image frame is defined as the count plus the standard deviation. Over all trials, this produces an average error of 7.4%, 5.2%, and 3.8% for the methods "without area," "with mean area," and "with median area," respectively. From trial 5 onwards, where the numbers of bats are larger and occlusion begins to be more important, the average errors are higher (9.3%, 6.2%, and 4.5%, respectively). Finally, we estimated the numbers of bats in the infrared thermal video recorded at Frio Cave (see online video

Table 1
Number of bats in the thermal infrared video recorded at Frio Cave using three counting methods. An error estimate based upon the simulation errors generated for each method is indicated in parentheses.

Counting method	Sum of # of bats in region O over all frames	Number of bats in final frame	Total # of bats in thermal infrared video
Mean	2060	1320 + (81)	3380 + (81)
Median	2066	1344 + (60)	3410 + (60)
Without	2285	1230 + (114)	3515 + (114)
Mean = 3435 + (85) = 3520			

Betke_BW_filtered_Frio.mpeg). The counting procedure indicates that the total number of bats present in the entire length of the video is approximately 3435 bats. This is based on averaging our results for the three counting methods (Table 1). The video counting methodology indicates that the number of bats in region O is relatively small (mean of 14.8 bats and a standard deviation of 3.3 bats). For these small numbers, the simulation regions provide percentage errors whose ranges are negligible. The simulation errors generated for each counting method produced error estimates that we applied to the results of these methods for the video recorded at Frio Cave (Table 1). When the errors are included and the results for the three methods are averaged, an upper estimate of 3520 bats was computed.

3.2. Moth-counting algorithms

The moth-counting algorithms were applied to process 3 video files of different lengths recorded in the field. The shortest video (3 min) is presented in the online material. Each video file was processed by the two relative-threshold methods and the automated-threshold method (Table 2). The number of moths estimated with these methods was compared using the "ground truth" number of moths present in each video, which we established by manually stepping through the saved frames (online-3mins-10-threshold-avg). The method with the smaller relative threshold of 5 grayscale levels was most accurate in estimating the number of moths in the videos. It detected 152 of 159 moths (95.6%) in a 1-h survey video. This method selected 10% of the total frames as relevant, while the other two methods selected only 5.5% and 2% of the total frames as relevant, respectively. Some moths that were too distant from the camera had pixel intensities almost equal to background and therefore were not counted by the thresholding technique that required a relatively high-intensity difference of 10 units. By lowering the threshold on the difference, it was possible to detect these moths. Using the automatic technique, some moths were missed because the threshold value determined by the algorithm was either too high or too low. Our results indicate that performing connected component labeling after thresholding eliminated a few unnecessary frames (these frames had images of one or two stars with no moths in them).

The time required to process the data with the relative-threshold technique is less than with the automatic threshold algorithm, which must first determine the threshold iteratively and then apply it to filter relevant foreground pixels.

4. Discussion

A basic tenet of ecology is to have accurate censuses of animals, including rare and elusive forms (Thompson, 2004), as well as relatively abundant and communal species (Kunz, 2003; Kunz et al., in press). Estimates of numbers of organisms are fundamental for many ecological applications, including population dynamics and determination of density dependent processes. A motivation for our simulation efforts and the basis for the above examples are to provide reliable estimates for agricultural pest insects and their predators. Estimates of abundance for pest species in conventional or transgenic crops are necessary to determine impacts of genetically modified crops and of the effects of predation by insectivorous bats and birds. The pest-control impact of bats can be significant from ecological, economic and evolutionary perspectives (Cleveland et al., 2006; Federico et al., 2008). A primary contribution of this paper is to address an unexplored link between simulation modeling and image processing by providing a framework for video censusing aggregations of organisms that include error estimates. This link between image processing technology and simulation modeling is relevant to organisms other than those illustrated herein with bats and their insect prey. The novelty of the approach is to simulate the video image by a mathematical model, which might prove to be a significant undertaking because a distinct model might be needed for each set of organisms to be censused. Thus, effort-benefit issues need to be considered when censusing highly mobile animals. Rule-based models seem well adapted to represent the behavior and movement of highly mobile organisms and thus to minimize efforts to construct models. These models make it possible to mimic aggregate dynamics and coupling with visualization and can produce error estimates in the numerical computation of aggregates. In the simulation model of our bat example, the rules of flight that the group of organisms exhibit appear to be well approximated. The flight behavior of Brazilian free-tailed bats as they emerge in columns is highly complex, and the primary rules of our model (Velocity Matching, Collision Avoidance, and Individual Predator Avoidance) yield complex dynamics appearing similar to those observed during an actual emergence. Without mimicking this flight behavior, the errors on the estimates of emerging bats present would not be as accurate or reliable.

There are methodological issues related to dynamic censuses of organisms displaying large communal flights that are of both

Table 2
Results from application of the three versions of the moth-counting algorithm.

Length of video	Thresholding algorithm (difference value)	Total # frames in video	Frames selected after thresholding	Frames selected after labeling	Moths in the video	Moths detected	Accuracy
3 min	Relative (5)	2,758	312	207	14	13	92.90%
	Relative (10)		26	21		9	64.90%
	Automatic	16	16		7	50.00%	
15 min	Relative (5)	26,882	3,120	3,052	37	33	89.20%
	Relative (10)		4,803	2,223		28	75.70%
	Automatic	633	236		17	45.90%	
1 h	Relative (5)	107,942	12,680	11,586	159	152	95.60%
	Relative (10)		17,973	8,577		136	85.50%
	Automatic		8,791	4,809		107	65.40%

theoretical and practical interest. The problem of undercounting because of full or partial occlusion in 2D videos remains an issue. Despite the use of pixel-area related estimates, our counting algorithm was inaccurate in frames where there was considerable overlap in projections of bats. We estimated the numbers of batoids in various simulation videos (Online Table 2). The videos of the simulations provided in the online materials (Online videos Simulation Side View and Simulation View from Above) contained 108 batoids and were composed of 247 frames (the number of frames is similar to the 225 frames of the video recorded at Frio Cave). Although the number of batoids in the simulation is significantly less than the number of bats in the Frio Cave emergence video, primarily due to the coupling of the simulation with the real time graphics, it indicates how our counting protocol handles occlusion. In the simulation, batoids were sporadically clustered to allow for possible occlusion of the batoids leaving the frame and those in the final frame. A multi-camera video recording and an associated counting procedure may help alleviate this problem, especially if 3D-visualization becomes feasible.

Another issue is that the flow rate of the bats in our example is not constant in all frames and the total number of bats estimated in the fixed-time video depends on the flow rate. A variable flow rate of bats leads to the number of individuals entering the frame being different from the number of bats leaving the frame, which can complicate reliable estimation of the number of individuals per frame.

The situation when organisms “escape” the camera’s focal length by moving out of vertical range does not occur for the thermal infrared video that we analyzed, but this could be a factor in undercounting for other videos. In video recordings in which bats leave the field of view at the upper edge of the image frame, a horizontal strip of pixels at the upper and lower edges could be used in addition to the vertical regions that we used in the present study.

The counting methodology based on the moth video did not employ a simulation model. This was rationalized by indicating the numbers are sparse and error bounds are small. While valid for our moth survey, this does not imply that error bounds are not important. Indeed, for rare, endangered or threatened species, organism numbers are small and discounting error estimates might suggest that the issue is not as critical to survival as the situation might actually be.

The contrast and speed of the video requires attention if moths are counted manually using a player such as Windows Media. Because of the low difference of intensity between the moth and the background and the short viewing period of a moth transecting the camera range, moths can be lost (even at the blink of eye) so the speed of the original video needs to be decreased when manual counts are made. Because it is difficult to detect the moths from the background due to the small differences in intensities, an option is to increase the contrast in the original video. Here, the contrast of the original video was not changed before applying the moth-counting algorithm using the application developed.

5. Conclusions

We conclude that the framework is applicable to many mobile organisms. It is generic because the methodology can be widely applied and need not be restricted to nocturnal species. Required for the framework is a database provided by a video of a behavior. The simulation procedure that is required could be labor intensive because it requires construction of a simulation model for the behavior of the video censused organism. Different behavioral processes such as the communal bat emergence investigated here and bat foraging, which is generally not done communally, could require different but related models.

Acknowledgements

The National Science Foundation grant ITR-0326483 (to T.H. Kunz, G.F. McCracken, M. Betke, J.K. Westbrook, and P.A. Morton) and the Cooperative Agreement CR 83214801 (to T.G. Hallam and G.F. McCracken) with the US Environmental Protection Agency provided funding for this study.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.ecocom.2009.05.012.

References

Baron, S., 1972. The Desert Locust. Scribner, New York, p. 228.

Betke, M., Hirsh, D.E., Makris, N.C., McCracken, G.F., Procopio, M., Hristov, N.I., Tang, S., Bagchi, A., Reichard, J., Horn, J., Crampton, S., Cleveland, C.J., Kunz, T.H., 2008. Thermal imaging reveals significantly smaller Brazilian free-tailed bat colonies than previously estimated. Journal of Mammalogy 89, 18–24.

Cleveland, C.J., Betke, M., Federico, P., Frank, J.D., Gomez, I., Hallam, T.G., Horn, J., López Jr., J.D., McCracken, G.F., Medellín, R.A., Moreno-Valdez, A., Sansone, C., Westbrook, J.K., Kunz, T.H., 2006. Estimation of the economic value of the pest control service provided by the Brazilian free-tailed bat in south-central Texas. Frontiers in Ecology and the Environment 5, 238–243.

Cockrum, E.L., 1969. Migration in the Guano Bat *Tadarida brasiliensis*, 51. Miscellaneous Publications, Museum of Natural History, University of Kansas, pp. 303–336.

Davis, R.B., Herreid II., C.F., Short, H.L., 1962. Mexican free-tailed bats in Texas. Ecological Monographs 32, 311–346.

Federico, P., Hallam, T.G., McCracken, G.F., Purucker, S.T., Grant, W.E., Nelly Correa-Sandoval, A., Westbrook, John.K., Medellín, R.A., Cleveland, C.J., Sansone, C.G., López Jr., J.D., Betke, M., Moreno-Valdez, A., Kunz, T.H., 2008. Brazilian free-tailed bats (*Tadarida brasiliensis*) as insect pest regulators in transgenic and conventional cotton crops. Ecological Applications 18, 826–837.

Hallam, T.G., Raghavan, A., Dimitrov, D.T., Federico, P., Qi, H., 2006. Technology and simulation of bat population dynamics. In: Tian, H. (Ed.), Proceedings of the Second IASTED International Conference on Environmental Modelling and Simulation. ACTA Press, pp. 113–117.

Kunz, T.H. 2003. Censusing bats: challenges, solutions, and sampling biases. In: O’Shea, T.J., Bogan, M.A. (Eds.), *Monitoring Trends in Bat Populations of the United States and Territories: Problems and Prospects*. U.S. Geological Survey, Biological Resources Discipline, Information and Technology Report, USGS/BRD/ITR-2003-003.Sciences Division, Information and Technology Report, Washington, DC, pp. 9–20.

Kunz, T.H., Whitaker Jr., J.O., Wadanoli, M.D., 1995. Dietary energetics of the Mexican free-tailed bat (*Tadarida brasiliensis*) during pregnancy and lactation. Oecologia 101, 107–115.

Lee, Y.-F., McCracken, G.F., 2002. Foraging activity and resource use of Brazilian free-tailed bats *Tadarida brasiliensis* (Molossidae). Ecoscience 9, 306–313.

Lee, Y.-F., McCracken, G.F., 2005. Dietary variation of Brazilian free-tailed bats links to migratory populations of pest insects. Journal of Mammalogy 86, 67–76.

Kunz, T.H., M. Betke, N.I. Hristov, M. Vonhof, in press. Methods for assessing colony size, population size, and relative abundance of bats. In: Kunz, T.H., Parsons, S. (Eds.), Ecological and Behavioral Methods for the Study of Bats, 2nd ed. Johns Hopkins University Press, Baltimore.

McCracken, G.F., 2003. Estimates of population sizes in summer colonies of Brazilian free-tailed bats (*Tadarida brasiliensis*), In: O’Shea, T.J., Bogan, M.A. (Eds.), Monitoring Techniques in Bat Populations of the United States and Territories: Problems and Prospects. Information and Technology Report USGS/BRD/ITR 2003-0003, pp. 21–30.

Mehmet Sezgin, B.S., 2004. Survey over image thresholding techniques and quantitative performance evaluation. Journal of Electronic Imaging 13, 146–165.

Qi, H., 1999. A High Resolution, Large Area, Digital Imaging System. Ph.D. Dissertation. North Carolina State University, Raleigh.

Rainey, R.C., 1989. Migration and Meteorology. Flight Behavior and the Atmospheric Environment of Locust and Other Migrant Pests. Clarendon Press, Oxford.

Reynolds, C.W., 1987. Flocks, herds, and schools: a distributed behavioral model. SIGGRAPH ‘87 Conference Proceedings, Computer Graphics 21 (4), 25–34.

Rosenfeld, A., Pfaltz, J., 1996. Sequential operations in digital picture processing. Journal of the ACM 13, 471–494.

Russell, A., McCracken, G.F., 2006. In: Zubaid, A., McCracken, G.F., Kunz, T.H. (Eds.), Population Genetic Structure of Very Large Populations: the Brazilian Free-tailed Bat *Tadarida brasiliensis*. Functional and Evolutionary Ecology of Bats. Oxford University Press, New York, pp. 227–247.

Sanchez-Arroyo, H., 2005. Largest Swarm. Chapter 27. University of Florida Book of Insect Records, Gainesville.

Schorger, A., 1955. The Passenger Pigeon. Univ. of Wisconsin Press, Madison.

Sullivan, J., 2004. Hunting for Frogs on Elston and Other Tales from Field & Street. Univ. of Chicago Press, Chicago.

Thompson, W.L. (Ed.), 2004. Sampling Rare or Elusive Species: Concepts, Designs and Techniques for Estimating Population Parameters. Island Press, Washington, DC, USA.

Westbrook, J.K., Wolf, W.W., Lingren, P.D., Raulston, J.R., Lopez Jr., J.D., Matis, J.H., Eyster, R.S., Esquivel, J.F., Schleider, P.G., 1997. Early-season migratory flights of corn earworm (Lepidoptera: Noctuidae). Environmental Entomology 26, 12–20.

Whitaker Jr., J.O., Neefus, C., Kunz, T.H., 1996. Dietary variation in the Mexican free-tailed bat, *Tadarida brasiliensis*. Journal of Mammalogy 77, 716–724.

Wolf, W.W., Sparks, A.N., Pair, S.D., Westbrook, J.K., Truesdale, F.M., 1986. Radar observations and collections of insects in the Gulf of Mexico. In: Danthanarayana, W. (Ed.), Insect Flight: Dispersal and Migration. Springer-Verlag, Berlin/Heidelberg, (AN00075), pp. 221–234.