An Adaptive Autonomous Aerial System for Dynamic Field Animal Ecology Studies

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***Abstract*—This work focuses on the optimization of aerial system controls and the design of autonomous navigation models for dynamic field animal behavior studies. Unmanned aerial vehicles (UAVs) can easily traverse remote terrain and quickly navigate around occlusions to collect imagery for animal ecology studies. Multiple UAVs, or a swarm, provide multiple views of group-living animals, providing richer insight into animal behaviors in the wild. However, animals are dynamic and unpredictable, requiring system control and autonomous navigation models capable of adapting to dynamic scenes. Here, I present my on-going work building such a system and corresponding autonomous navigation models, and detail future plans.**

I. Motivation and Challenges

UAVs have been used for animal population counts [6], behavior studies [9], [16], pose estimation, [26], and to infer the social dynamics of group-living animals [23]. UAVs are adaptable to a large variety of species and habitats, such as birds, including penguins and albatrosses [5], [11], marine animals, including sea turtles, seals, and whales [8], [10], as well as terrestrial animals, including zebras, giraffes, baboons, yaks, and Przewalski's horses [9], [16], [21], [23]. However, the vast majority of these animal ecology studies rely on manually piloted, single-UAV missions, which are not scalable.

Multiple UAVs, or swarms, overcome the challenge of the limited flight time of a single UAV working alone, enabling the collection of large-scale, high resolution spatiotemporal datasets. Autonomous UAVs can collect large volumes of data with greater consistency and reliability compared to manually piloted missions [19]. Furthermore, autonomy is required to conduct highly dynamic missions that would be impossible for human pilots to conduct unassisted due to the highly dynamic nature of the environment and the objects under surveillance. However, little guidance exists on optimizing aerial system controls and designing autonomous navigation models to conduct animal ecology studies. The aerial system must coordinate the UAVs to collect a comprehensive view of the dynamic scene, while avoiding collisions and managing battery levels efficiently. In addition, field animal ecology studies are conducted in areas with few compute resources, requiring an Edge AI approach to enable low-latency inference for the autonomous navigation models.

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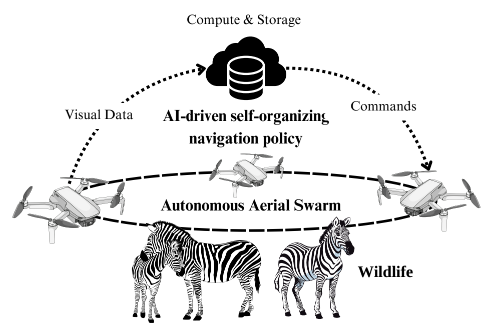

Fig. 1. Design of Autonomous Aerial System for Animal Ecology

II. Contribution and Objectives

My research focuses on the following objectives: 1) the design of adaptive, autonomous navigation models for UAVs in a dynamic context, and 2) the system controls for coordinating autonomous aerial swarms on the edge. The main contribution of my research is an end-to-end autonomous, aerial system for field animal ecology studies, illustrated in Figure 1. Previous works have approached the problem of monitoring animals with UAVs from a computer vision perspective [21], [23], [25]. My approach complements and builds on existing projects, such as WildDrone [1], by approaching the challenge of monitoring animals with UAVs from an autonomous systems control perspective. In my previously published work [18], [19], I focus on the application of existing computer vision models to build autonomous navigation policies to dynamically gather animal ecology data with drones. I will build on this autonomous navigation model by adding effective swarm coordination systems controls and considering the hardware and network constraints of executing navigation models on the edge.

III. Methodology and Preliminary Results

In January 2023, I traveled to the Mpala Research Centre in Laikipia, Kenya, to collect video data of zebras and giraffes with UAVs. We published the dataset produced by this study, KABR: In-Situ Dataset for Kenyan Animal Behavior

	Herd Tracking [19]	Herd Tracking + Telemetry [18]	Performance Gain
Accuracy	68.8	87.0	+18.2
F-1	82.1	90.4	+8.3

TABLE I
AUTONOMOUS NAVIGATION MODEL PERFORMANCE [18], [19]

Milestone	Timeline
Develop behavior-adaptive navigation	Spring-Fall '24
Develop individual id navigation	Fall '24 - Spring '25
Test behavior-adaptive navigation	Summer '25
Test individual id navigation	Summer '25
Develop end-to-end integrated system	Fall '25 - Spring '26
Test integrated system	Summer '26

TABLE II
SCHEDULE OF MILESTONES

Recognition from Drone Videos [16] and demonstrated the advantages of using data collected with UAVs to study animal behavior over traditional data collection methods [14]. Building on my experience manually piloting UAV missions in Kenya, I designed a navigation model using YOLO [15], a popular light-weight objection detection and classification model, to autonomously track herds [19], which recreated flight paths with a 68.8% accuracy, Table I. Next, I analyzed the KABR telemetry dataset [20] to characterize the missions that best captured behavior data. Integrating these findings into the autonomous navigation model from [19], improved its accuracy by 18.2%, as shown in Table I. I collaborated with Dr. Pianini and his team from the University of Bologna to integrate KABR data [20] into the Alchemist simulator [24] for decentralized multi-drone coordination for animal video acquisition [7].

A major challenge in deploying dynamic, adaptive autonomous aerial systems in remote regions are the very limited memory and compute resources [12]. To overcome this challenge, we designed a *distributed edge AI system* optimized for field animal ecology studies with autonomous aerial systems, which is currently in submission [13]. We implement distributed AI inference on the edge to maximize the limited compute and memory resources available. This distributed computing approach will enable the deployment of more sophisticated autonomous navigation models in the future, such as the decentralized multi-drone coordination model proposed in [7]. Our design is motivated by the unique compute requirements for animal ecology study workloads, which we use to model and provision edge resources. We developed an analytic model to guide the deployment of remote, edge resources to support autonomous aerial swarms for field animal ecology studies.

IV. FUTURE WORK AND RESEARCH PLAN

A. Autonomous navigation and system control policies

Behavior-adaptive: A significant concern in deploying UAVs for animal ecology studies is the potential disturbance to the animals [3], [4], [22], [25]. For animal behavior studies, it is crucial that the UAVs be non-disruptive to avoid artificially inducing vigilant or evasive behaviors in the wildlife. For this challenge, we propose a multi-agent reinforcement learning (MARL) *behavior-adaptive navigation policy* which dynamically adjusts the aerial system's movements to avoid inducing behavior in the animals. We use non-deterministic finite-state machines (FSM) to model animal behavior with a wide variety of possible behavior distributions to account for differences due to habitat or demographic class. We aim to demonstrate that our proposed FSM formulation of behavior is general enough to model a variety of species in different habitats, and that existing MARL algorithms can covertly observe targets. A MARL approach simultaneously handles the autonomous navigation and the system control to coordinate the UAVs for field animal ecology studies.

Individual identification: The individual identification of animals is a powerful tool for accurate population estimates and is an active area of computer vision research. Animals with distinctive morphologies, such as zebra's unique stripe pattern or a whale's unique fin shape, can be individually identified and re-identified, from photographs [2]. The ability to individually identify animals from UAV videos would offer new opportunities for accurate population counts [6] and fine-grained analysis of group dynamics [23]. However, tracking herds and navigating UAVs to capture multiple photographs suitable for individual identification is a challenging systems control problem. I have partnered with a group of computer vision experts developing AI models for the detection, tracking, viewpoint classification, and individual identification of animals. I will use the output of these AI models to inform the autonomous aerial system for *individual identification navigation*, building on my previously published work [17], [19]. This approach will expand on the aerial systems control methodology previously proposed in [19].

B. Field testing

I am currently testing the autonomous navigation policy proposed in [19] and refined in [18] on the zebra and giraffe herds at The Wilds, a 10,000-acre conservation center located in Ohio [27]. In the future, I plan to *test these navigation policies and system control techniques* at The Wilds. I have obtained approval from The Wilds to study the Grevy's zebras, giraffes, onagers, Przewalski's horses, and African Wild Dogs.

C. Schedule of milestones

My planned work is summarized in Table II. The system control policies and autonomous navigation models described in Section III and IV-A are developed and tested virtually in simulation. Next, they will be tested at The Wilds during summer months while the animals are in pasture. The final phase of my thesis will integrate the distributed edge AI design, autonomous navigation models, and systems control policies to create an adaptive autonomous aerial system for dyanmic field animal ecology studies.

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