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Acoustic, Seismic, and Visual Camera Sensor Fusion Experiments for Large Animal Detection and Tracking with Scalability

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Prior research efforts to detect and track large animals have relied upon a combination of ground, aerial, and satellite remote sensing. For example, detection of elephants and human activity to help with the prevention of the poaching of elephants and rhinos for their tusks and horns has focused on large scale sensor networks that are multi-domain (ground, aerial, satellite, perimeter fencing). These networks show promise, but data from satellite and aerial domains can be expensive, subject to limitations of weather, terrain, and foliage challenges, whereas interior mesh and perimeter sensors can offer cost and performance advantage, but only if spatial scaling can be achieved. While all sensor domains are likely to provide valuable information for game parks, ranches, and farms that need wide area large animal monitoring, the interior mesh sensor networks can be improved by combining sensing modalities to go beyond common practices like use of camera traps. In this paper, we examine cost effective methods to build multi-modal ground sensors for open range interior mesh use, which combine seismic, acoustic, and visual sensor data to improve large animal detection, and re-detection within scalable mesh networks for tracking. The experimental sensor network is focused on open range interior mesh nodes including nodes in an edge, fog, and cloud hierarchical network to enable scaling to larger areas. The scaling of interior mesh sensors provides improved spatial coverage, combined with high fidelity spectral and temporal resolutions possible with edge computing in a multi-modal sensor assembly described along with methods of sensor and information fusion. The use of multi-modal, scalable mesh sensor networks is compared to multi-domain methods in terms of overall cost and performance. The goal is to evaluate whether the fusion of all these sensing modalities would improve detection and lead to a significantly reduced response time from game reserve, ranch, or farm personnel to resolve issues with large animal health and safety. Preliminary field tests in northern California focused on use of mesh sensor assemblies that combine seismic, acoustic, and visual sensing are described along with preliminary testing and performance results. Future work will focus on evaluating the scaling and efficacy of this design at a game reserve in South Africa.

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I.Nomenclature

ALSA	=	Advanced Linux Sound Architecture
Edge	=	Sensor with interfaces only to other mesh sensors, low power, and simple single sensing mode
ERP	=	Elephants, Rhinos, and People
Fog	=	Sensor node with uplink to Internet and interface to other sensors in an extended mesh
FoV	=	Field of View
GPS	=	Global Positioning Satellite System
GPSD	=	Global Positioning Satellite System Daemon (software service)
GPU	=	Graphics Processing Unit
LED	=	Light Emitting Diode
LIDAR	=	Light Detection and Ranging
LoS	=	Line of Sight
LTA	=	Long Term Average
ML	=	Machine Learning
MQTT	=	Message Queue Telemetry Transport
NEMA	=	National Electrical Manufacturers Association
NIR	=	Near-Infrared
PCM	=	Pulse Code Modulation
RADAR	=	Radio Detection and Ranging
RF	=	Radio Frequency
RGB	=	Red, Green, Blue
ROS	=	Robot Operating System
SSD	=	Single Shot Detector (Neural Network)
SSIF	=	Sensor System and Information Fusion
STA	=	Short Term Average
UART	=	Universal Asynchronous Receive and Transmit
UAS	=	Unmanned Aerial System
UAV	=	Unmanned Air Vehicle
USD	=	US Dollar
UTC	=	Universal Coordinated Time
YOLO	=	You Only Look Once (Neural Network)

II.Introduction

Elephant and rhino populations have been cut down to about 5% of what they were at the turn of the 20th century [1]. With poaching rates as high as four elephants killed every hour and five rhinos a day in 2016 [1], it is possible for these animals to become extinct in the wild soon. Elephant tusks and rhino horns are highly sought after in Asian countries such as Vietnam and China, a demand that drives poaching in African nations [2, 3]. Coupled with this demand is the problem of poverty in southern Africa, where the average annual income is about USD 1,700. With the price for a pair of elephant tusks nearly USD 50,000, and that of a rhino horn around USD 360,000, the motivation to become involved in poaching is clear [1].

To combat poaching, both short-term and long-term strategies need to be employed. Approaches such as education, poverty alleviation, and eradication of demand are viable long-term solutions. In the short-term, however, poaching prevention and animal conservation are crucial to protect these animals for generations to come. The present research effort is focused on the use of sensor fusion, sensor networks, machine learning, and computer vision to provide game reserve personnel with real-time information for timely intervention and prevention of poaching. This paper in particular focuses on preliminary field testing of ground sensor networks, conducted in northern California at the California State University farm in Chico, to collect and analyze sensor data for sensor fusion to detect, track, and monitor large animals.

Our current research effort seeks to develop a sensor network that uses sensor fusion methods to monitor animals. We are particularly interested in detecting and monitoring large animals located within a large space such as a farm or wildlife reserve. We are interested in collecting data related to ground motion, acoustics, and ground level images. Our first field test seeks to have one of our sensor nodes deployed at a farm and left to collect raw data for an extended period of multiple months. Our first field trial node consists of a geophone which aims at detecting changes in ground motion caused by animal locomotion. Similarly, we are testing microphones to detect vocal cues emitted from animals as well as acoustics caused by the animal movement. Furthermore, our sensor node also consists of an RGB camera which can acquire a visual depiction of the environment as the acoustic and seismic signals are collected.

The purpose of the research presented in this paper is to gather ground sensor data from acoustic, seismic, and visual sensors to explore methods of sensor fusion to improve methods of large animal detection and tracking in large spaces. The long-term goal is to contribute to the preservation of elephants and rhinos, and to keep elephants, rhinos, and people out of conflict.

A. Review of Literature for Large Animal Ground Sensor Networks

Poaching detection and prevention sensor technologies can be categorized as either perimeter based, ground based, aerial-based observation, or animal tagging. In a previous paper [4] we reviewed work from each of these categories. Since this paper is more focused on ground-based sensors and systems, this literature review follows suit.

Within the category of ground-based sensors, visible and infrared, acoustic, and seismic sensors have been considered. A combination of these and more sensors was assessed by Kim et al. [5] along a perimeter. Their combined sensor event detection algorithm with the sensor combination reduced the false positive rate of human and vehicle detections. Among the sensors used were acoustic and seismic.

Seismic sensors have been used to detect elephants and study their behavior in prior research [6]. Both elephant vocalizations and locomotion can be detected by seismic sensors. Elephant vocalizations are characterized as low-frequency rumbles that propagate through the earth. Applying a propagation model to geophone recordings the authors of Ref. [6] estimated propagation ranges of cow vocalizations to be greater than 6 km. The propagation distance is affected by soil type, and detection limited by background noise. Variability of seismic detection ranges was noted in Ref. [3].

Lamb et al. [7] investigated the use of a Raspberry Shake and Boom (RS&B) sensor for detecting elephant vocalizations and locomotion. The RS&B is composed of a vertical geophone and omnidirectional pressure sensors for infrasonic acoustic waves. The pressure sensors of the RS&B unit had limited success in detecting elephant vocalizations, attributed to high daytime temperatures and wind conditions attenuating the low-frequency sounds. The authors also noted the low sampling rate (100 Hz) of the unit did not allow for higher harmonics to be recorded. The geophone success was also limited by the low sampling frequency, but it was able to detect animal locomotion within 50 m of the sensor. Improper ground coupling may have been the reason for the low success rate compared those reported in Ref. [6], thus the authors suggested the use of a concrete vault as a remedy.

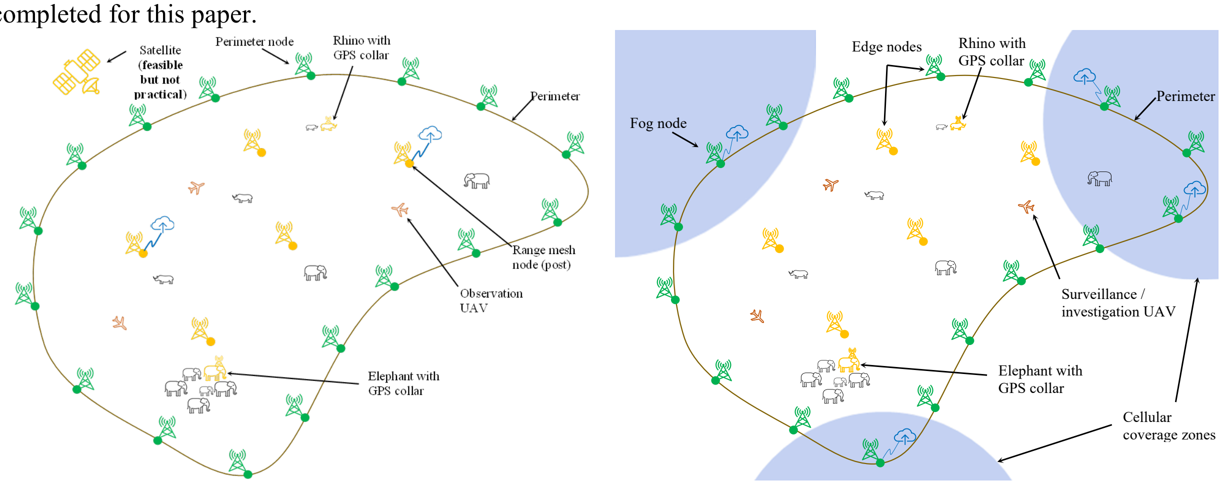
The use of acoustic sensors to detect elephants was considered in Ref. [8] wherein the authors researched methods for detecting the presence of elephants to serve as an early warning system. Acoustic detection focused on low-frequency (10-30 Hz) vocalizations from elephants as these had been shown to travel distances of up to several kilometers. Using a support vector machine, the authors reported an 88.2% detection rate and a 13.7% false-positive rate. Challenges discovered by the researchers were that cars and airplanes produce low-frequency noise, and that elephant vocalizations occur infrequently. The authors thus recommended the combination of acoustic detection with visible detection. For visible detection, the authors exploited both color and temporal cues applied to video of animals in their natural environment. Observations were categorized as either near (<50 m) or far (>50 m). The detection rate in the near range was 91.7% with a 2.5% false-positive rate; in the far range the detection rate was 88.0% with a 39.0 % false-positive rate. The authors concluded that acoustic and video detection should be combined for improved performance, and that thermal sensors should be evaluated as an additional future sensor.

The authors of Ref. [9] made use of infrared cameras as part of a Wireless Image Sensor Network (WISN) for wildlife monitoring in Mongolia. Each node within the network had an infrared camera combined with pyroelectric infrared sensors, light sensors, and infrared LEDs. The pyroelectric infrared sensors had a sensing angle of 120° and were configured to provide omnidirectional coverage. Upon animal detection by the pyroelectric infrared sensors, a servo would rotate the camera to the appropriate viewing angle and collect an image. Each node also included an ARM7 processor, a ZigBee transceiver, and a solar battery. The nodes were configured in a mesh topology allowing for multi-hop transmission to a fog node that included a 3G cellular connection. Network implementation or simulation was not presented in the paper.

Ground-based sensors offer high temporal and spatial resolution, but limited coverage. Combining multiple sensors can reduce false positives and configuring ground sensors in a network can provide wider coverage. Seismic sensors show promise due to the size and unique vocalizations of elephants, but factors such as soil type and anthropomorphic noise sources need to be considered for sensor deployment. Combining acoustic and visible sensors can increase animal detections. The experimental focus of this paper is field deployment of a Fog node consisting of a geophone, microphone, and visible RGB camera that can also interface to simpler single sensor Edge nodes and provide uplink of processed data to the Cloud.

B. Prior Work on ERP (Elephants, Rhinos, and People)

Prior work on the ERP sensor network focused on satellite images, fence vibration monitoring, and use of ground level camera traps. The experience gained from this Phase-A study noted in Ref. [4] and analysis of results lead our research team to conclude that while satellite monitoring is feasible (elephants and vehicles can be detected and even counted), it is not practical given the cost of the images ($500 for 25 square kilometers for one date) and given ground foliage, uneven terrain, and weather conditions which occlude the animals of interest and evidence of human activity in unexpected locations. As shown in Fig. 1, the original architecture has been simplified to eliminate satellite images, replaced by reliance on UAV systems launched for specific incident coverage, and organized into Cloud, Fog, and Edge nodes. The Cloud nodes are simply web pages accessible by game management via Internet for situational awareness, the Fog nodes are sensors that are multi-modal (camera, microphone, geophone, and fence vibration) and are placed on the perimeter of the park with cellular uplink to the Cloud (fence mounted when possible), and the Edge are single mode sensors (microphone, camera, or geophone) that are lower power and use Zigbee mesh communication to Fog nodes. A comparison is provided in Fig. 1 between the original concept and the revised based on research completed for this paper.



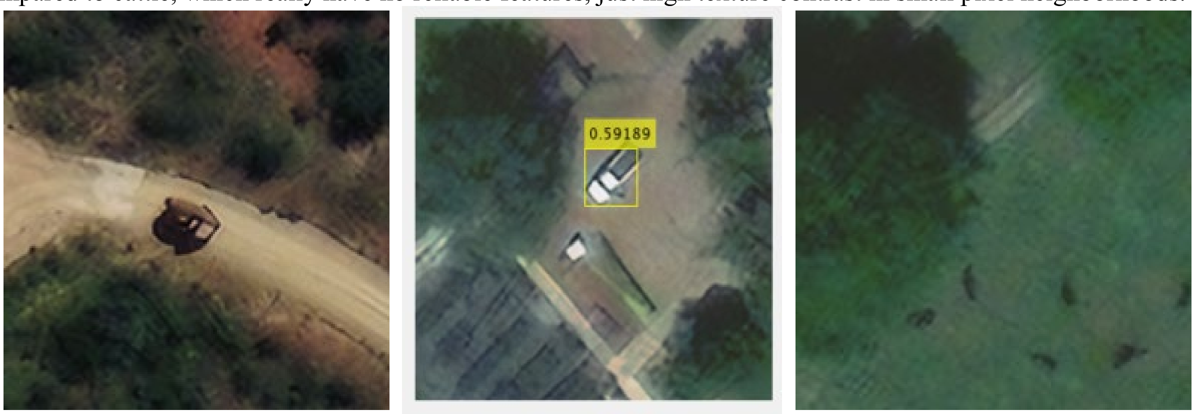
(a) Original satellite, UAV + ground sensor concept; (b) Revised Cloud, Fog, Edge node concept with UAV

Fig. 1 Overview of Complex Multi-Domain, Multi-Modal Anti-Poaching Sensor Network Comparing Original Phase-A and Revised Phase-B Concept Based on Elimination of Satellite Sensing, Addition of Cellular, and Differentiation of Node Types as Cloud, Fog, or Edge Nodes

The Cloud nodes provide access to data made available as web services including back-end database (SQL) and front-end (Python Django) presentation for browsers. A Cloud node therefore is accessible worldwide to anyone with proper credentials with Internet access. The Fog nodes are multi-sensor nodes comprised of two single board computers, namely a Raspberry Pi and an "NVIDIA" Jetson Nano, and may include a full complement of sensors (fence vibration, subterranean geophone, microphone(s), and motion trigger smart cameras). The two boards are connected via an ethernet connection. The main purpose of the Raspberry Pi is to support the geophone. We are using a system developed by Raspberry Shake, S.A, which is suited to working with the Raspberry Pi. The geophone is connected to the Raspberry Pi via a UART connection. The cameras used are connected to the Jetson via a CSI and/or USB connection, and the microphone and GPS via USB. Each Fog node includes a Zigbee/XBee mesh sensor node communication gateway via mesh scalable XBee RF links to Edge nodes. Fence vibration nodes will be treated as Edge nodes so they can scale out from a Fog node along the fence using Zigbee/XBee protocol for triggered event notifications. Edge sensors will only have Zigbee/XBee in a mesh configuration and will provide simple activity alert notifications to Fog nodes. The Edge sensor nodes will be single-sensor and send event metadata to the Fog node gateway node over a low-power IEEE 802.15.4 wireless communication protocol (i.e., XBee module). The Fog node gateway is responsible for uplink of the data from each sensor node to the Internet Cloud services via cellular connection (e.g., 5G UW provided by Verizon in the current test configuration). The Cloud services will aggregate, process, and present the data in a yet to be fully determined fusion method on a dashboard.

To summarize the prior Phase-A experiment of Ref. [4], the conclusion overall is that while satellite detection of elephants and vehicles is feasible, smaller animals (e.g., cows) is less feasible based on small pixel size in images.

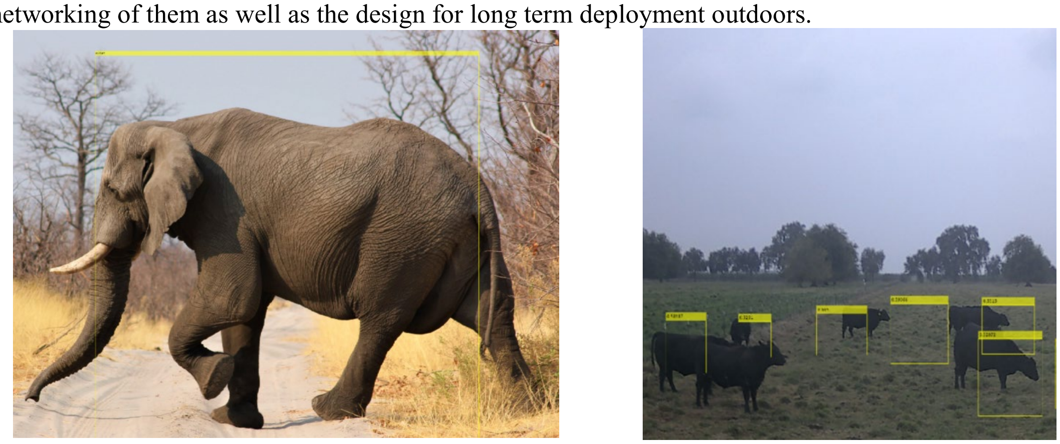
Even for larger elephants, the terrain, foliage, and weather often occlude them for any given observation. Finally, the cost of satellite images ruled this sensing method out, despite the superior spatial coverage of an entire park in one image at 30 cm/pixel resolution. Fig. 2 summarizes example results and shows the feasibility for elephants and vehicles compared to cattle, which really have no reliable features, just high texture contrast in small pixel neighborhoods.



(a) Image of Bull Elephant (b) Example Detection of Vehicle (c) Cattle Image (Small Pixel Size)

Fig. 2 Phase-A Example Satellite Image Detection using Deep Learning (SSD and YOLO Transfer Learning Networks) – Based on Premise that Cattle are a Proxy for Elephants and Rhinos

Ground cameras, microphones, and geophones were the experimental focus of the Phase-B research presented here given the success of fence vibration monitoring in prior work noted in Ref. [4] and the impracticality shown for satellite image processing. Fig. 3 shows examples from Phase-A experiments with ground cameras which show feasibility and the promise of sensor fusion methods such as Deep Learning with neural networks. Given the success of the ground cameras, our research group decided to focus fully on ground level cameras and the Cloud-to-Fog-to-Edge networking of them as well as the design for long term deployment outdoors.



(a) Ground Detection of Large Elephant (b) Ground detection of smaller Cattle

Fig. 3 Phase-A Deep Learning Visual Detection of Large Animals (Ground Camera)

The original attraction to our research group to satellite imagery was based on prior related research [10], as well as the goal to detect vehicles in unexpected locations, and given the superior spatial coverage of satellite images compared to ground camera images. As can be seen in Fig. 3, the ground camera detection is reliable and feasible at a much lower cost than satellite observation if cameras are placed in a mesh network. Spatial coverage can be improved for ground cameras by fully surrounding the perimeter of a game park with camera nodes separated no more than 1 km apart, based on the Zigbee/XBee mesh communication ranges tested in Phase-A and noted in Ref. [4]. Prior work on the LoS detection of objects of interest in images such as drones that are much smaller than elephants show that a 1 km camera mesh is feasible – further separation will result in failure to observe even large animals, since they will register less than a single pixel in an image as described in Ref. [11]. Furthermore, the cameras can be placed and provide better temporal coverage when motion triggered and combined with fusion methods such as Deep Learning evaluated in Phase-A.

Finally, the field testing of Phase-B smart cameras (custom cameras with filtering and motion trigger software), the geophone, and microphones in a test Fog node revealed that it was impractical to not have any Internet connection. Reasons included inability of difficulty with in-place software upgrades and updates, severe weather that made manual data collection a challenge (corroded connectors), and issues with convenience for data collection on a regular basis. Based upon related research of large-scale sensor networks are described in Ref. [12], the concept of Cloud-Fog-Edge sensor scaling such that the Fog nodes provide a gateway to Cloud services and to interior mesh or perimeter mesh nodes out of cellular range became attractive. Further, in our test location in Chico California, 5G UW (Ultra-Wideband) Internet services made the use of a hot-spot convenient and simplified coordination. Research of the availability of hot-spot cellular Internet services in South Africa revealed that at game parks such as Rietvlei, similar (lower bandwidth 4G LTE) coverage is likewise available and will continue to evolve toward 5G UW in more areas over time. Elimination of cost related to satellite coverage may be offset by costs of cellular Fog-to-Cloud gateways for Edge mesh data, but the more continuous temporal coverage looks promising. Future Phase-C work will focus on more analysis of the Cloud-Fog-Edge scaling, but preliminary results at our test site indicate this is an interesting alternative for scaling coverage.

As noted in this prior work summary, the past experiments have focused on Deep Learning methods and feasibility testing camera traps, fence vibration monitoring, and use of satellite images from these three different domains. The current experiments presented in this paper have focused completely on ground sensor networks of multi-modal sensor assemblies that include a combination of a seismic geophone, acoustic microphones, and visual cameras (potentially multi-spectral) to determine the best methods for ground-based detection and tracking of large animals. While ground sensors do not provide the coverage of satellite images, ground sensors can be expanded in a mesh topology using Zigbee/XBee and make use of edge machine vision and machine learning. Related research has shown that these mesh networks can scale even more with fog computing [13, 14] and cloud computing to provide monitoring of larger areas at costs that are competitive with multi-domain monitoring. The rest of this paper therefore focuses on what we designed for the ground Cloud-Fog-Edge sensor network, what we learned about ground node challenges, and preliminary data we collected, and how our new experience has helped our research group to outline a follow-on Phase-C and additional Phase-B data collection to follow this presentation of results.

To summarize the status of the Phase-A focus on Deep Learning and satellite image analysis with ground camera traps, here is our analysis of feasibility:

1) **Satellite**: feasible [4, 14], but not practical due to cost and limited availability (weather, terrain, foliage).
2) **Ground RADAR and LIDAR**: not practical due to cost, but better if UAV based as noted in Ref. [11].
3) **Fence Vibration**: accelerometer sensors with Zigbee/XBee line-of-sight communication for mesh scaling – feasible and practical at fenced game parks such as Rietvlei.
4) **Camera traps**: used with Deep Learning post processing for detection and classification of animals and threats to them – feasible and practical (state of practice), but mostly forensic rather than real-time incident response.
5) **Sensor Local storage**: manual data retrieval is practical, but inconvenient and high latency for real-time response to an incident (forensic only).

Based on Phase-A results our team hypothesizes that the optimal set of cooperative (complimentary) sensors for Phase-B SSIF will be:

1) **Multi-spectral Imagers**: Upgrade from camera traps to custom multi-spectral NIR and visible camera systems with motion triggers with custom filtering.
2) **Acoustic**: Add microphones for short range sensor fusion with camera detection of animals, people, and vehicles described in Ref. [15].
3) **Seismic**: Add below-ground geophones along boundaries and occasionally interior for large animal and vehicle detection for sensor fusion with cameras.
4) **Fence Vibration**: Retain and improve fence vibration sensors for perimeter use for intrusion detection.
5) **Aerial**: Fixed wing drone surveys for incident response (state of practice), equipped with RADAR or LIDAR as noted in Ref. [11].
6) **Hybrid Sensor Network:** Cellular, 802.11, and Zigbee/XBee communication for Cloud-to-Fog-to-Edge sensor network processing.

The combined sensors list above for Phase-B continued investigation with bench testing and field trials reported in this paper. Follow-on Phase-C work is envisioned to include simulation of the use of these key cooperative sensors for SSIF at the scale of a game park such as Rietvlei. The SSIF design that has been evaluated in Phase-B from the bottom up, is envisioned to enable further research for pattern analysis and situational awareness summaries for Cloud dashboards for real-time incident response as described in prior surveys and research on SSIF architectures described in Ref. [16].

III.Ground Sensor System and Information Fusion

Given the goal to focus fully on ground sensors with the vision to eventually simulate or build a scaled-out Cloud-to-Fog-to-Edge sensor network, our research team decided to focus on the Fog node first, since it serves as a gateway (bridge) between the Cloud and Edge nodes. The Fog nodes are also envisioned to provide the first level of sensor and information fusion, whereas Edge nodes will likely use triggering and provide raw data (images, audio samples, seismic activity, or vibration) by event. The Fog nodes could provide pattern analysis or contextual logic (e.g., an unexpected vehicle detection in the vicinity of elephants) to filter down data that would be uplinked to the Cloud.

A. SSIF Model and Sensor Network Architecture

A well-known SSIF (Sensor System and Information Fusion) architecture is the Waterfall model as shown in Fig. 4. The waterfall will ideally focus game wardens on incidents with the greatest threat of potential poaching.

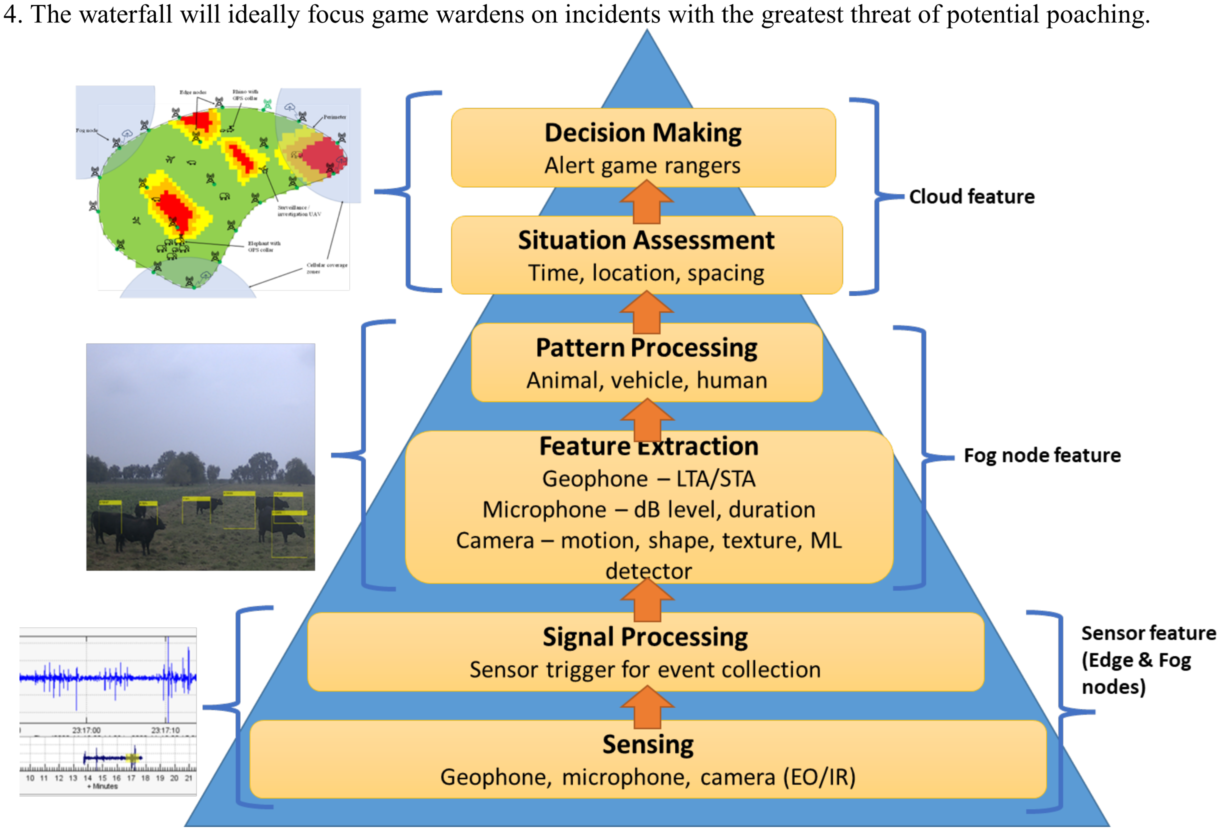


Fig. 4 Waterfall Fusion Process Model Applied to the Current System

Rather than trying to work top-down from Deep Learning, Dempster-Shafer as noted by Buede et al. in Ref. [17], Bayesian inference, or simple signal level filtering, our team decided to work bottom-up and from the Edge to the Fog nodes with focus on lower-level sensor networking layers of basic sensor assemblies and signal processing using basic filters and triggers. For example, the geophone LTA/STA (Long-Term and Short-Term Average) intensity trigger, acoustic spectral band, and intensity triggers, and filtered motion triggers for cameras. Software was developed as noted in Ref. [18], where each sensor can potentially operate alone, single mode for the Edge, with GPS for time and date correlation, in a SSIF complimentary sensor network. The Fog node built and evaluated to date simply aggregates Edge data and integrates all the basic ground sensors into a single node (acoustic, visual, and seismic). All the triggers are asynchronous in the results gathered in the bench testing and field testing completed to date, so GPS is the only way to "fuse" the data by time and location within the Fog-to-Edge network. The Fog node first level of more advanced SSIF will focus upon feature extraction as shown in Fig. 4. Further work is required to evaluate pattern processing, and would require use of Deep Learning, Dempster-Shafer, Bayesian inference, or more sophisticated filters (e.g., Kalman for vehicle or aircraft tracking). The model discovered during the build-up from the bottom approach presented here lead to realization that this classic SSIF model for complementary sensors (compared to competitive or cooperative) fits our overall goals for game park situational awareness and decision making by Cloud users quite well.

The SSIF network designed to include a Cloud-to-Fog-to-Edge architecture, where situational awareness of the large animals to be protected and potential threats are summarized, is envisioned to translate into alerts and a heat-map of threats available as a web service on the Internet. The SSIF is based upon the Edge sensor nodes using an XBee/Zigbee mesh network that in turn interfaces to Fog nodes (mostly on the perimeter but placed anywhere with cellular Internet gateway potential). The Edge nodes are envisioned to be single sensors nodes for simplicity that have simple triggers for detection of large animals and human activity. The trigger logic for the geophone is based upon LTA/STA intensity, the trigger logic for acoustic on frequency bands and intensity, and motion based for camera edge nodes. These edge node events have been logged and uploaded by Fog nodes in bench and field testing to date, which could be extended to make use of more advanced inference methods such as Dempster-Shafer or Deep Learning used in prior work noted in Ref. [4], to note incidents of high interest in the local region of that mesh. For example, unexpected vehicle activity (based on location), presence of large animals, and proximity of vehicle activity to the animals.

B. Senor Network for Game Parks

Based upon limited cellular coverage and internet services in game reserves, the architecture is a Cloud-to-Fog-to-Edge network, as described in Ref. [13], where Fog nodes must be placed in areas of game reserves that have cellular internet access as shown in Fig. 5.

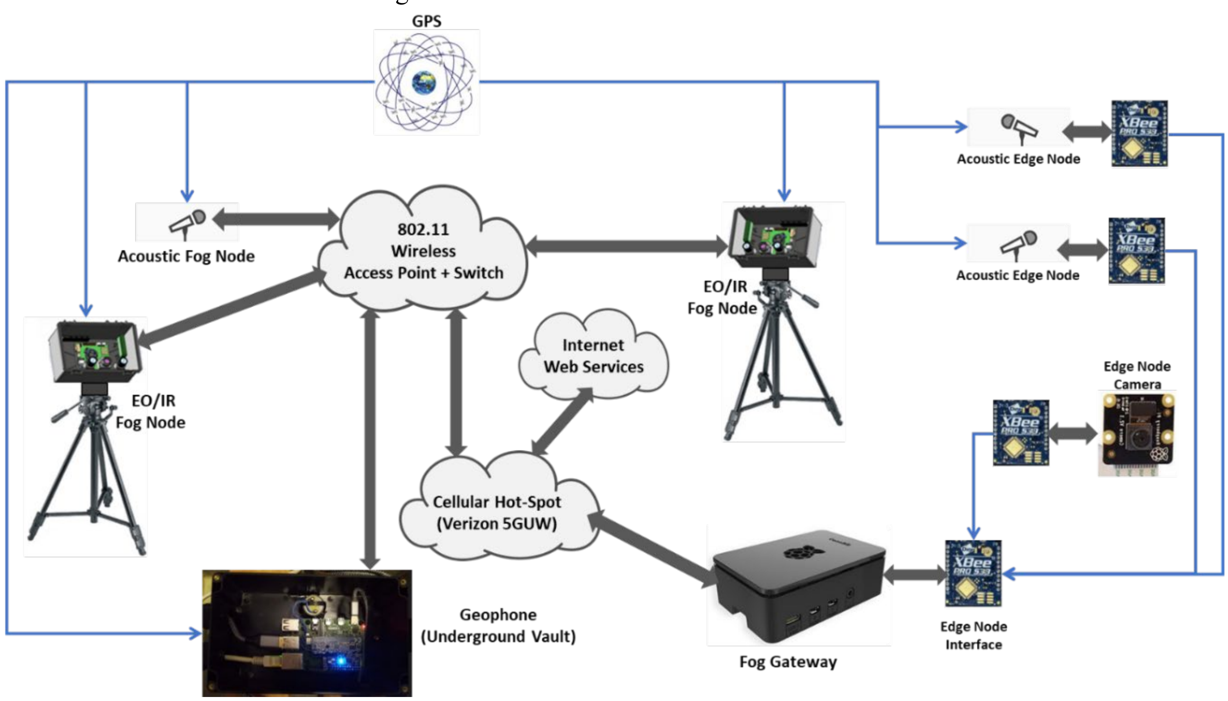


Fig. 5 Fog-to-Edge Sensor Network Architecture where Fog Nodes provide Cloud Uplink

Fig. 5 was built out for bench testing and limited field testing (based upon weather conditions and other challenges discussed more in results in this paper) to the Fog-to-Edge gateway. The Fog-to-Edge gateway could be a custom software node but can also simply be purchased as an XBee "DigiMesh" gateway as noted in Ref. [19]. While the test location at the California State University farm in Chico is not as remote as some South African game parks, it is comparable to the Rietvlei game park, and based upon success using 5G UW cellular for Cloud-to-Fog networking at the CSU Chico farm, the research group is planning more testing and will likely rely upon cellular internet in the first small scale tests planned for South Africa in summer 2024.

To summarize the elements of the Cloud-to-Fog-to-Edge sensor network architecture, the goal is to build nodes as follows:

1) Fog nodes have cellular Internet uplink and/or aggregate data from the mesh nodes, and have both XBee point-to-mesh and 802.11 / cellular Internet uplink interfaces, with the following additional features:
    a) Solar or grid power (higher Wattage requirements with RV class 12 volt and higher amp-hour capacity).
    b) Combined sensors possible in a single node (acoustic, camera, geophone, and fence vibration).

c) Deployed anywhere where cellular services are available on the perimeter of a game park or interior, no closer than 1 Km apart, but less frequently placed.
   d) Uplink to web is event driven and filtered or pattern based.
2) Edge nodes have only mesh XBee point-to-point, line-of-sight, and single instrument, and low-power solar (backpacker class 5-volt fifty amp-hours) with the following additional features:
   a) Solar power must be stand-alone.
   b) Interior use, so tree, pole, structure mounts used.
   c) Single instrument – microphone, camera, or geophone for simplicity (power limitations, failure modes, and networking).
   d) Must have line of sight to an Edge node (single hop MQTT) or to another mesh node (multi-hop MQTT).
   e) Uplink to Edge node or adjacent mesh node is periodic or event driven.
3) All nodes have GPS for complimentary sensor time correlation.
4) A Fog-to-Edge gateway can be an off-the-shelf DigiMesh network element or software defined.

Fig. 6 shows a simplified networking model for the Fog-to-Edge network protocols. The 802.11 and 5G UW were evaluated in the current configuration to obtain results reported in this paper, and XBee was not evaluated, but was range tested point-to-point in prior work described in Ref. [4].

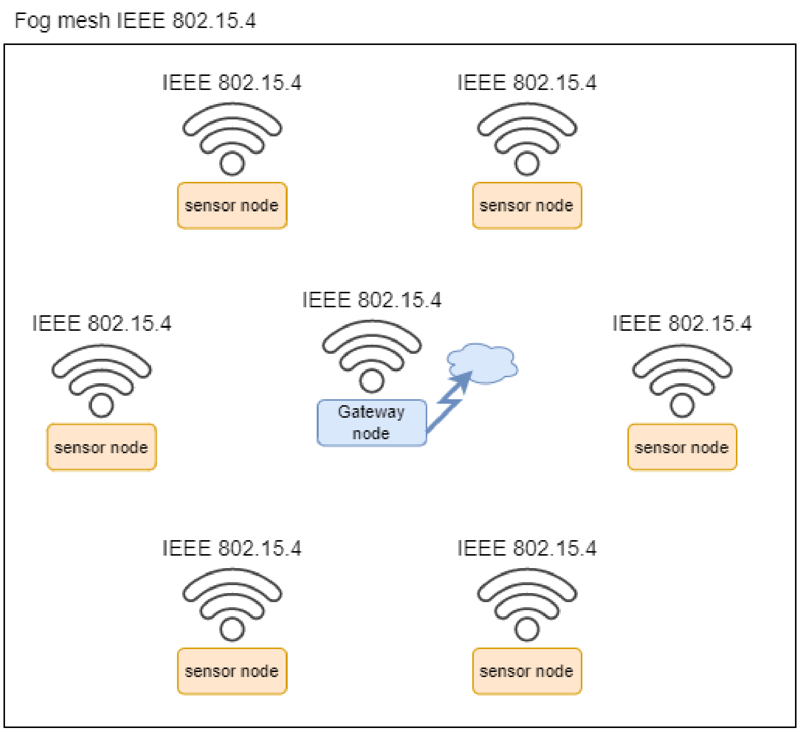


Fig. 6 Fog-to-Edge Mesh Network Diagram Scalable with XBee DigiMesh

C. Fog Node Design

Given that the geophone had not been field tested before, the results reported here primarily focus on the below ground deployment of the geophone in a Fog node as shown in Fig. 7. The exact field test configuration for the results in this paper include what is shown "Below Ground" and the solar panel and USB GPS receiver.

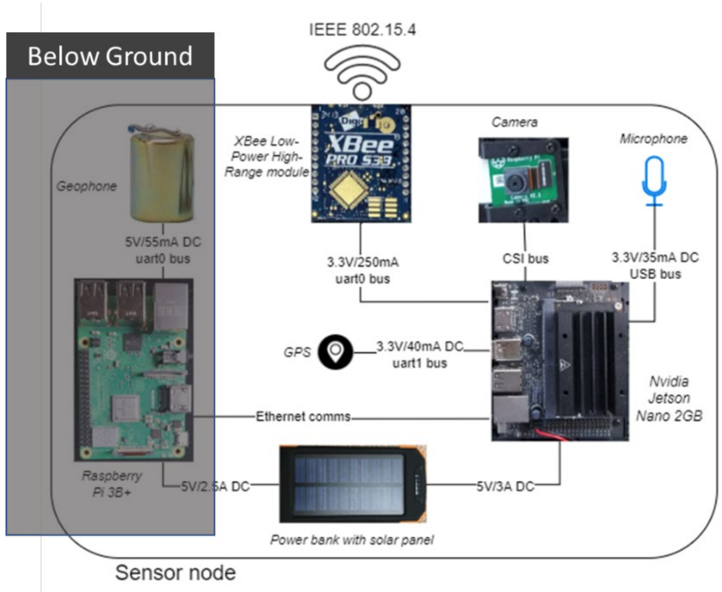


Fig. 7 Fog Node to Edge Mesh Test Configuration (Bench) and Below Ground (Field Test)

While the "Below Ground" portion of Fig. 7 is just one of the subsystems in a full-scale Fog node, the construction and field testing was non-trivial.

Fig. 8 Geophone Vault Integrated into Fog Node – Below Ground Fog Node Realization

Based upon prior work noted in Ref. [7], the research group built a cinder block vault and buried the geophone three feet underground as shown in Fig. 8. The above ground pole added to the CSU Chico farm fence was used for solar power, test cabling, and GPS so that cattle could not disturb these above ground elements. As can be seen in Fig. 8, the vault includes the geophone in a NEMA enclosure to prevent water intrusion and corrosion. The vault was determined to be "over-built" as discussed in results and survived well and after 3 months of deployment in rain, heat, and day-to-night cycles, the sensor assembly contained in the unit was still fully functional. However, the above-ground test connectors corroded and continuous challenges with connector corrosion have revealed that all connections required NEMA protection.

Phase-A camera traps have been upgraded to custom camera nodes that include NIR (Near Infrared) and visible cameras in a common NEMA enclosure with motion trigger software used to detect objects of interest with filtering for false triggers. False triggers noted in Phase-A not only included animals that are not of interest, but also wind blowing grass, clouds, and other background motion. Simple filtering methods such as erosion filtering as noted in Ref. [20] and statistical change thresholds are used in custom camera traps which can be tuned for specific objects of interest (elephants, rhinos, vehicles, people). While a Fog node can be scaled-up to be a multi-modal sensor assembly at an individual location with cellular services, the research team envisions expansion into the interior of the park or between Fog nodes with Edge nodes.

D. Edge Node Design

The Edge node design starts with a simple gateway between a Fog node with 802.11 or wired ethernet to a Zigbee/XBee mesh of single-sensor nodes that must be placed in trees or on the ground, with limited power.

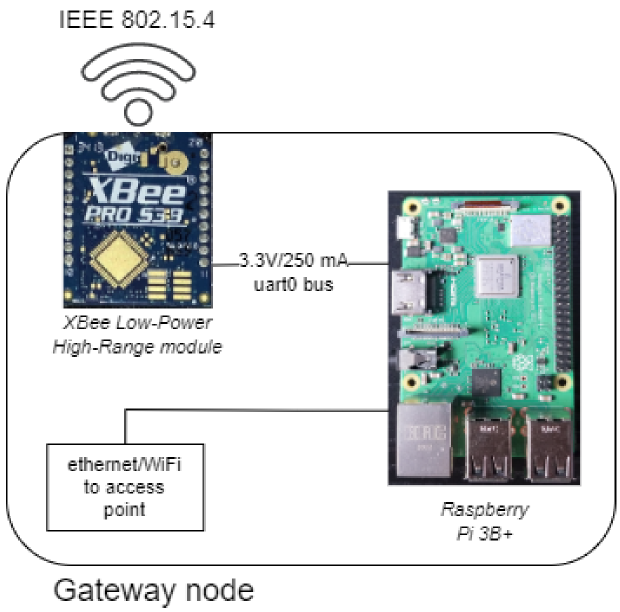


Fig. 9 A Gateway Node Block Diagram

To build out the Fog-to-Edge network to the low power single sensor Edge nodes, use of a DigiMesh Zigbee/XBee network element or a software defined gateway is envisioned, but not yet bench or field tested as shown in Fig. 9. Phase-B includes the addition of new field sensor testing of microphones that are triggered by intensity in specific frequency bands of interest. Based upon the challenges of the Fog node cellular uplink, test interface corrosion, solar power limitations (with backpacker class units), the field results are limited to and focused upon the geophone. Prior work with outdoor cameras and microphones noted in Ref. [15], have shown that above ground camera enclosures and microphones can survive for multiple seasons outdoors. The Jetson Nano 2GB shown in the Fog node in Fig. 7 will be used to do most of the edge processing using the 128 GPU cores, manage visual and acoustic sensors, manage timing specification in real-time using GPS receiver, manage IEEE 802.15.4 communications with the gateway node, as well as fusing the data from the seismic sensor sub-module (e.g., Raspberry Pi Shake). The power bank is responsible for delivering power to all the components within the sensor node. The low power IEEE 802.15.4 wireless communication protocol (i.e., XBee module) is used to communicate with other sensor nodes. The access point near the gateway node enables forwarding the data sent/received from the sensor nodes to the cloud. The gateway is powered using the grid either directly via a dedicated power supply, or Power over Ethernet. The Fog-to-Edge mesh network enables each sensor node to communicate metadata to the gateway node over a low-power IEEE 802.15.4 wireless communication protocol (i.e., XBee module). It is the gateway node's responsibility to forward that data to the cloud for further processing and visualization.

IV. Bench and Field Test Configuration and Experimental Results

The experiments completed by the team and results can be divided into bench tests (all Phase-B sensors individually) and field tests (emphasis on the geophone) and bench analysis of integrated, but asynchronous triggering of each sensor. The goal for outdoor field testing required significant effort in packaging for all three main sensors (camera, microphone, and geophone) using NEMA enclosures, powering off the grid with solar, and mounting the sensors on fencing at the CSU Chico farm. Given the unexpected challenges with the geophone, the camera and microphone sensor were only bench tested, in part due to higher confidence in their outdoor use outside of areas with cattle, based upon prior work noted in Ref. [15].

A. Experimental Field Test Software Configuration

Fig. 10 illustrates an elephant passing by two nodes with different sensor configurations at various times. Each sensor module logs the sensor data and GPS acquired UTC when triggered.

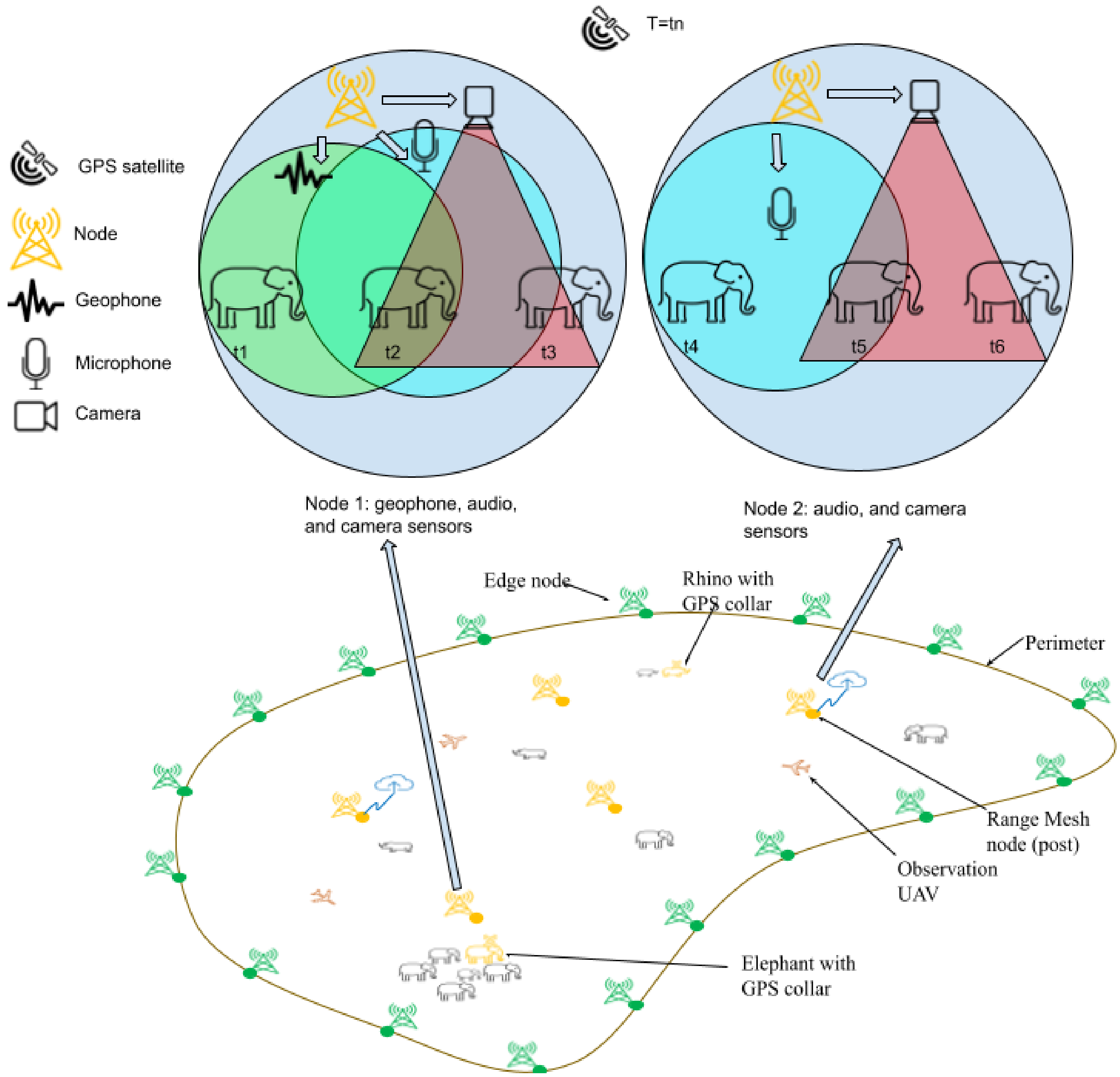


Fig. 10 Conceptual Cooperative (Complementary) Multi-Modal Sensor Triggering

The primary experimental design required development and integration of software for each Phase-B sensor (acoustic, camera, and geophone) and trigger logic for detection of events that indicate the presence of the large animals of interest or human activity. The Edge nodes are single sensors based upon size and power constraints compared to Fog nodes most often placed on the perimeter of a game reserve in cellular coverage areas in areas with roadway access. The Edge nodes will be a single geophone, camera, or microphone array. In a configuration where all three basic sensors are combined into a Fog node, the geophone will have below and above ground components as well as cellular uplink to the Cloud.

A geospatial range as depicted in Fig. 10, may contain several nodes with any combination of audio, visual, and/or geo-phone sensors. As each sensor runs on its own embedded Linux microprocessor, there may be significant differences between the internal clocks of sensors both within and between nodes. We incorporate GPS modules into each sensor module to use UTC (coordinated universal time) to synchronize sensor timestamps across the asynchronously triggered sensors.

When a target object emits enough sound, ground vibration, or motion within range of a microphone, geo-phone, or camera sensor, respectively, the sensor is triggered to log the event data along with a GPS acquired UTC timestamp.

Sensors are triggered asynchronously and may have varying detection ranges. "Node 1" of Fig. 10 illustrates a Venn diagram of an elephant causing the three types of sensors of a node to trigger at times t_n. At time t_1, only the geo-phone sensor is triggered while at time t_2 all three sensors of the node are triggered.

While the field testing of the Fog-to-Edge node test for this paper is not yet complete, the bench-test results and initial geophone field test results have helped the team to improve the design for physical challenges such as connector corrosion and depth of the below-ground geophone. As the Fog-to-Edge sensor network is scaled up and out, the focus in a follow-on continuation of Phase-B will be methods to aggregate asynchronous trigger events and data into higher level sensor fusion pattern analysis as shown in Fig. 4. The Cloud-to-Fog-to-Edge sensor fusion network will work bottom up to detect elephants, rhinos, and people with accuracy and reliability such that the higher-level pattern and situational awareness sensor fusion can alert game wardens to potential incidents. Audio, visual, and geophone sensor data are used in a cooperative (complimentary) fashion to detect the presence of objects of interest.

Prior work on the use of motion-based triggering for multi-spectral cameras combined with microphone arrays as noted in Ref. [15] has shown feasibility for reliable detection of objects of interest. This method may result in false negatives and false positives when a target object enters a data capture range causing short-term acoustic stimulation, ground vibration, or changes in the visual field of view, but the triggers can be tuned to detect significant changes in the data streams. This is best done on-site where the sensors will be deployed based upon environmental parameters where they will be used (lighting, background noise, and ambient ground and fence vibrations).

Sensor fusion algorithms may utilize data from homogeneous sensors, known as a competitive configuration and/or from diverse types of sensors known as a complimentary configuration. These algorithms process all input data and produce a prediction that is expected to be no less accurate or dependable than a prediction based on data from a single sensor. We focus on a complimentary configuration for target object detection utilizing the three sensor modalities previously described.

Using the GPS modules as a single point of truth for time, each sensor module could use time-series data for feature extraction and pattern discovery from the sole source data, and each node can then compute a situational assessment and decision making with multi-source data correlation from time t_n to time t_{n+1}.

B. Description of Below-Ground Geophone and Field Data Collected

The seismic submodule consists of four main components: a geophone, Analog to Digital UART converter, Raspberry Pi, and GPS module. To timestamp the seismic data, the Raspberry Pi needs to be connected to a network time protocol server. Since the node is designed for remote deployment, we acquire time for a GPS module connected via USB. We use a combination of two software tools: 1) GPSD and 2) "Chrony" to acquire time from the GPS module.

Additional modifications entailed turning the Raspberry Pi to an access point using "HostAPD" software. This configuration allowed for easy bench testing since connection to the Raspberry Pi could be achieved without the need for a tether.

In our prior work as noted in Ref. [4], we outlined the algorithmic approach for the trigger that would be used to acquire and then process the seismic waveforms collected by the geophone. The Raspberry Pi has a "SeedLink" software server running onboard. Seismic data is then sent over a socket from the SeedLink server to a circular buffer. Once in the buffer, a high pass filter of 40 Hz is applied to the data. Next, we use the STA/LTA triggering algorithm to discern whether an event has occurred or not. To distinguish various events, for example one that is caused by a person traversing the ground or another caused by motor vehicular traffic, we run simultaneous STA/LTA triggers with different averages.

Data collected to date in Phase-B has been less than planned based upon challenges with field sensor deployment. The data collected has primarily been bench testing for the camera and microphone with emphasis on the least understood and most risky deployment of the below-ground geophone. As detailed here, we found that we buried the geophone too deep.

C. Deployment of Below-Ground Geophone at CSU Farm

Phase-B has focused on the test deployment of a single multi-modal Fog node with an underground geophone and above ground camera and microphone wireless nodes that are all connected via 802.11 to a 5GUW Internet hot-spot. The most complex field deployment was the underground geophone in the concrete vault. The deployment, shown in Fig. 11, was made in early August of 2022 and the vault was retrieved in late November 2022.

Fig. 11 Geophone Installation in Underground Vault

Subsequent analysis of the vault has shown that we buried the geophone much deeper than was necessary to conceal it and protect it from the weight and impact of the animals and vehicles. The vault survived well for the three months it was deployed for field testing, but the data gathered was minimal, but additional bench testing using the same unit that was deployed has been included in this paper. Further, since the unit survived well, it is ready to be re-deployed in early 2023 in a much shallower pit, with upgrades to address challenges encountered with solar power and connector corrosion.

Fig. 12 shows an example of the short duration data collected at the 3-foot depth.

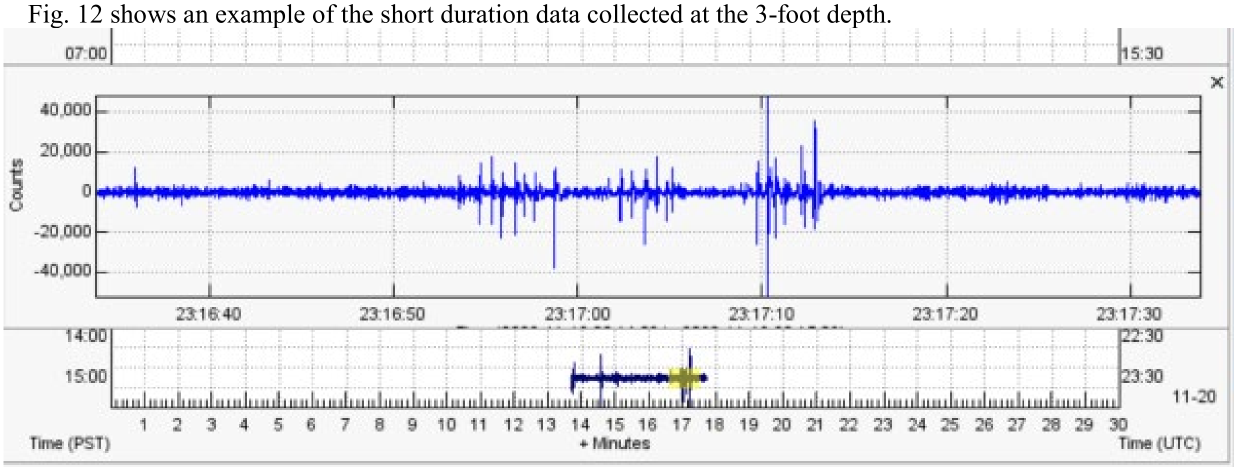


Fig. 12 Minimal Geophone Data Collected In-situ at 3-foot depth

Due to issues with connectors between the solar panel power banks (USB 5 volt) and the below-ground unit, power was not dependable without cleaning of the connectors with anti-corrosive compounds, and at best, data was collected for short durations. Further, retrieval of that data was complicated due to Ethernet RJ-45 connector corrosion, which was worse than the USB power and GPS data connections (normally left connected). This was due to the occasional use of this test connector only when a field laptop was used to retrieve data from the geophone below ground.

This activity was not sufficient to characterize the seismic activity of animals (cattle) that regularly stood over and walked on top of the ground above the unit. We realized the vault was too deep and while it was well protected, we dug it up and subsequently completed a mechanical analysis which shows a depth of six inches would be sufficient for use with cattle.

The first deployment of the geophone and vault placed it about three feet underground due to concerns over the vault collapsing under the weight of cattle walking over it. A mechanics of materials analysis has since been conducted to assess the strength of the concrete cap block that was used as the roof of the vault. The dimensions of the concrete cap block are as given in Fig. 13. The cap block was treated as simply supported along all edges with a uniformly distributed circular load applied at the center; this is a loading case for which a solution is provided in Ref. [21]. It was assumed that the load was applied over a 3-in-diameter circular area as an approximation of the size of a cattle hoof. The tensile strength of the concrete material was taken as 1.45 MPa based on Ref. [22].

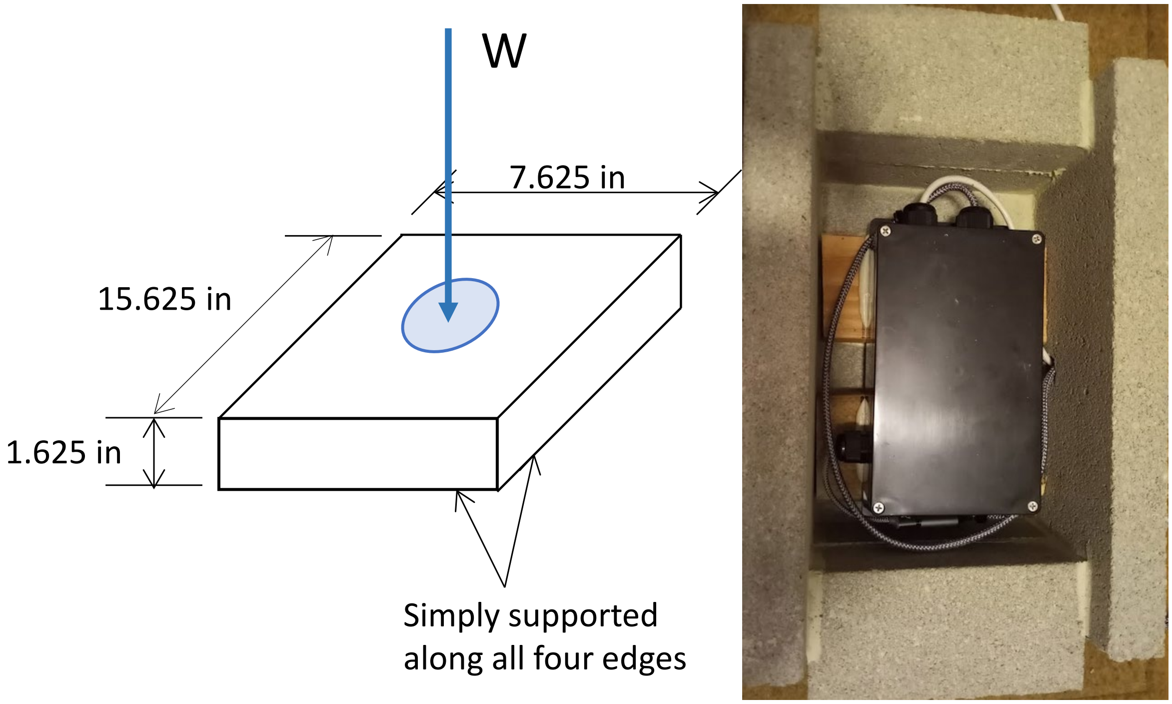


Fig. 13 Loading analysis of concrete cap block shown next to actual concrete block vault (cap removed)

With the above-described setup, the cap block can support 460 lb (2050 N). If the upper surface of the vault were to be placed two inches beneath the ground, it is estimated that the cap block would be able to support 630 lb. (2800 N); at a depth of four inches the cap block can support 830 lb (3700 N). The distribution of stresses in the soil was estimated using the 2:1 approximation method [23]. This analysis shows that the vault can be buried much closer to the surface than the initial deployment. The vault design focuses on simple construction using low-cost cinder blocks, readily available at any home improvement store using concrete glue to assemble the vault from these blocks. The NEMA enclosure for the geophone sensor electronics within the concrete vault protects the electronics, but the entire assembly is rigidly connected. Given the structural integrity based upon loading analysis, this vault can be buried much closer to the surface for simpler maintenance access and better detection of surface seismic activity. The vault was buried far deeper than it needed to be buried for our first field trial.

Given this depth of deployment design flaw in our first field test of the geophone, the research team reoriented focus upon bench testing and coordination of networking, in-situ software updates and upgrades, and evaluating the asynchronous trigger design that feeds into feature extraction in Fig. 4. The team plans to re-deploy the vault in a shallower pit in future testing.

V.Software and System Status and Bench Testing Results

The software system was evaluated for each sensor in an Edge node configuration and characterized in preparation for field testing. The field testing was completed using the subterranean geophone portion of a Fog node with solar power and cellular uplink networking. The camera and microphone subsystems were not field tested, just bench tested based upon challenges encountered with the geophone deployment. Those bench test results are summarized in this paper along with the initial field trial results for the geophone.

A. Geophone Bench Testing in Vault Configuration

As can be seen in Fig. 14, Fig. 15, and Fig. 16, adjusting the STA/LTA time windows influences the sensitivity of the triggering algorithm. The data was collected from a bench test where a human stomped near the vicinity of the geophone node. The geophone was located inside of the vault during this experiment. For triggering, we use the recursive STA/LTA algorithm as implemented in ObsPy [24].

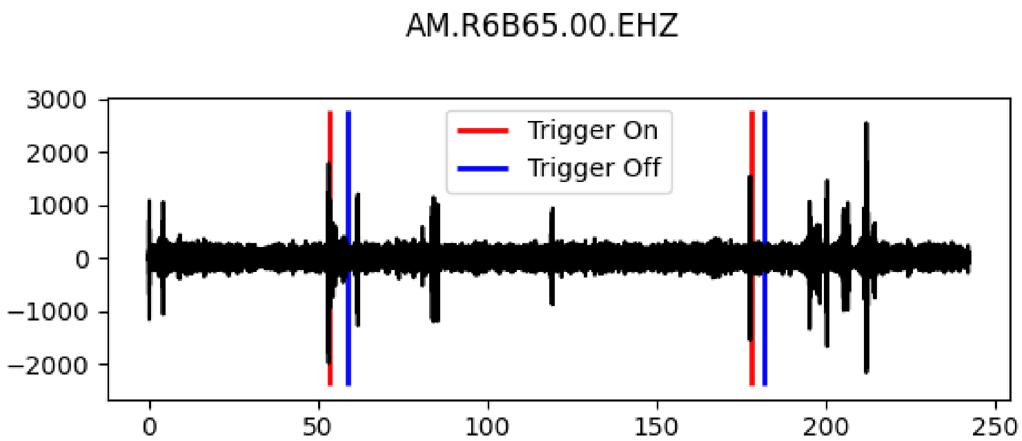


Fig. 14 STA=2, LTA=8, Threshold On = 2.5, Threshold Off = 1

In Fig. 14, the trigger detects smaller events, but not larger ones, as can be seen by the omission of the trigger on the right side of the graph. Going forward, using multiple thresholds for triggers seems like a viable option for distinguishing between animals. Lightweight animals would tend to cause small-scale events, whilst larger ones would induce stronger ground vibrations.

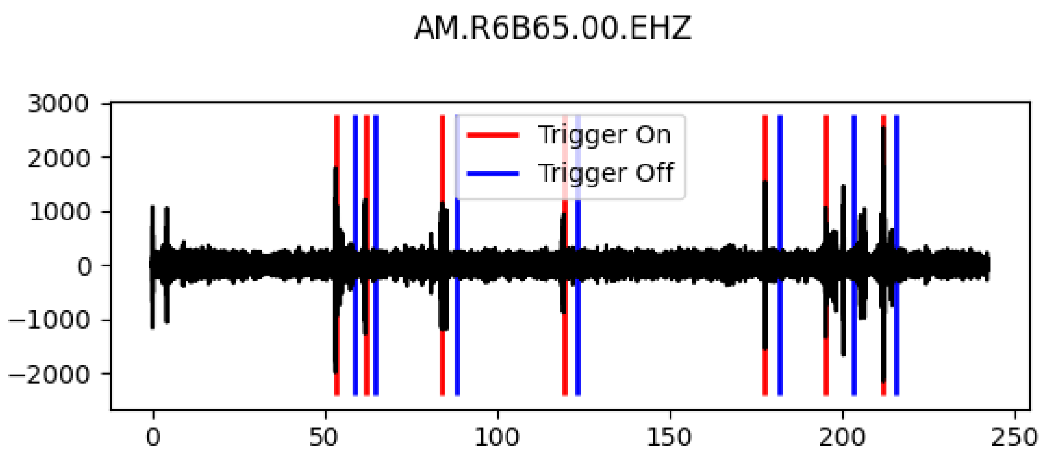


Fig. 15 STA=2, LTA=10, Threshold On = 2, Threshold Off = 1

A lower STA/LTA ratio renders the algorithm more sensitive to a wider range of events, as shown in Fig. 15.

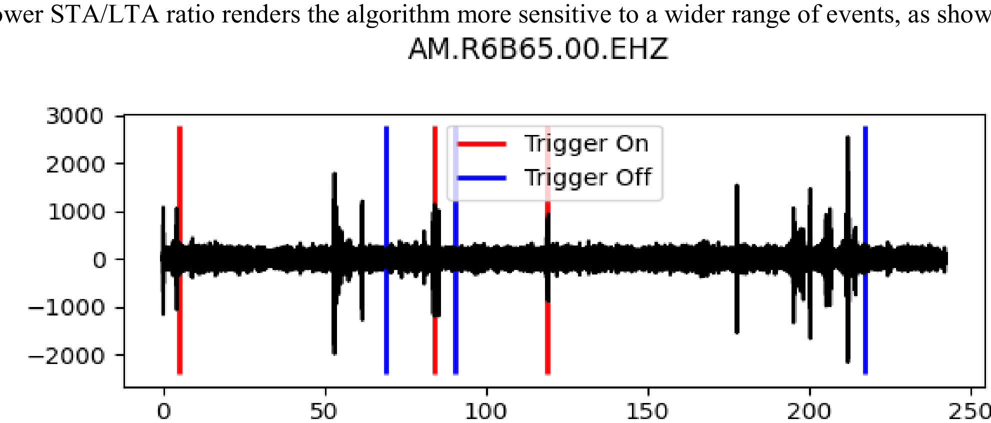


Fig. 16 STA=1.5, LTA=5, Threshold On = 1.5, Threshold Off = 0.5

After burial of the sensor node, we identified issues with field survivability. Firstly, the Raspberry Pi was not able to maintain a powered state for a prolonged period. The syslog indicated an under-voltage warning. One cause for this can be attributed to the fact that the GPS module and Geophone increased the power consumption of the unit and the solar powered battery pack used initially was not able to keep up with power consumption needs of the equipment. Additionally, connector issues meant that we were unable to SSH via ethernet. Improvements entail using a UART connection for console access.

B. Camera Bench Testing with Trigger Software and Dual Camera

The original camera traps used in Phase-A work are being replaced with custom multi-spectral motion-detect camera systems integrated in NEMA enclosures for solar powered field use as shown in Fig. 17.

Fig. 17 Images from USB Visible Camera Node – Showing Motion Detection of a Clock

The software has been updated to incorporate GPS time and location with date for triggered event recording of NIR and visible images as shown in Fig. 17 provided by software in Ref. [18]. The software is designed to run on an embedded Linux system (NVIDIA Jetson Nano) and makes use of a CSI/MIPI Raspberry Pi Noir IR camera and a visible USB camera in each enclosure running the motion detection application.

C. Microphone Bench Testing with Trigger Software

The acoustic trigger microphone software has been adapted from prior research for aircraft and drone localization using fused audio sound intensity and visual motion detection in prior work noted in Ref. [15]. The software has been updated to incorporate GPS time and location with date for triggered even recording with PCM data as found in Ref. [18]. The software is designed to run on an embedded Linux system (Raspberry Pi) and makes use of the ALSA sound capture software used with Raspberry Pi and USB microphones running the audio application. The bench microphone unit and a typical output intensity diagram is shown in Fig. 18.

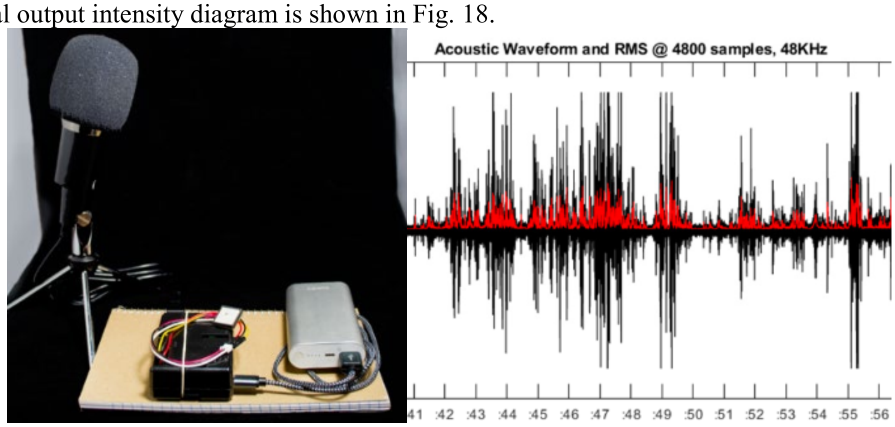


Fig. 18 Microphone System and Output Intensity Diagram

D. Integration of Asynchronous Triggers for Fog-to-Edge Node Scaling

Fig. 19 shows the use of each Edge node sensor (individual camera, microphone array, or geophone) along with aggregation into Fog nodes (multi-modal, multi-sensor nodes with cellular uplink to the Cloud).

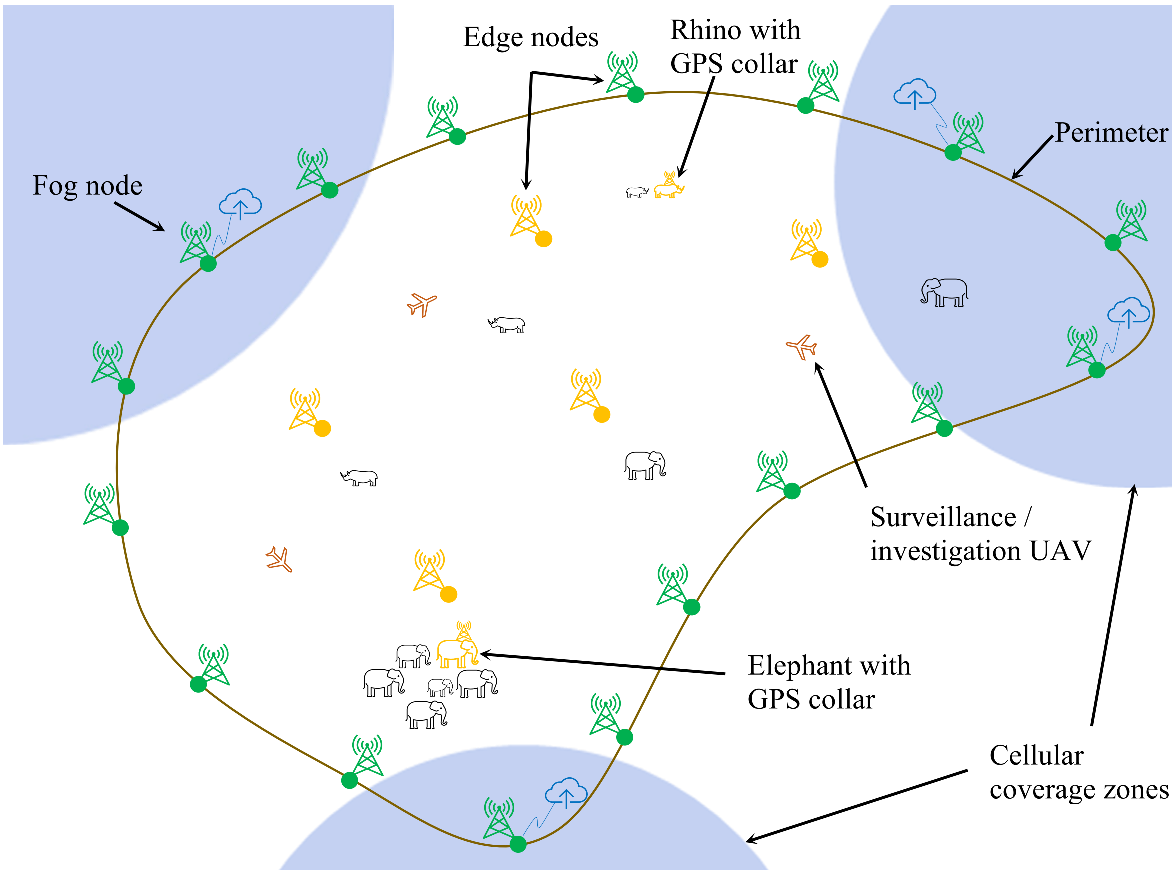


Fig. 19 Revised Notional Anti-Poaching System Based on Phase-B Testing

Based upon the limited field testing of the geophone and bench testing of all Phase-B sensors, the overall status of each sensor node element and Fog node, Edge node status has been assessed for continuation and completion of Phase-B field trials and advancement to Phase-C.

The key to the design is simplicity for Edge nodes which will be interior to the game parks with more challenging power and mounting scenarios with perimeter or occasionally interior mounting options (fences and towers) where more significant solar power and cellular uplink can be integrated.

VII. Future Sensor Network System Improvements and Cloud Access

Future work, planned as an effort to wrap-up Phase-B field testing of a single Fog node and Fog-to-Edge node configuration at the CSU Chico farm, with follow-on to better assess scaling, will start in early 2023 and continue through summer and fall of 2023. Scaling with sensor hardware is expensive, and the planned trip to South Africa for summer 2024 will also make full scale testing at the goal location prohibitive. Based on the cost challenge, the research team is planning to focus on fidelity of Fog-to-Edge field testing and scale-up of just one node, but with the goal to import the performance into a simulation of full-scale use at the Rietvlei game park.

A. Cloud View of Game Park with Heat Map

The heat map will be derived from Fog node aggregated events from Edge node signal processing and will be based upon Fog node feature extraction and pattern analysis. The majority of the high-level SSIF may be done in the Cloud for Deep Learning or other SSIF compute intensive analysis, although the Fog node Jetson unit can do machine learning detection and classification given the Jetson co-processor scaling. The idea for the heat map is that overall, the highest levels of Fig. 4 SSIF should filter down to situational awareness with the potential to grade events and incidents between nominal, warning, and dangerous situations by location in each game park as shown in Fig. 20.

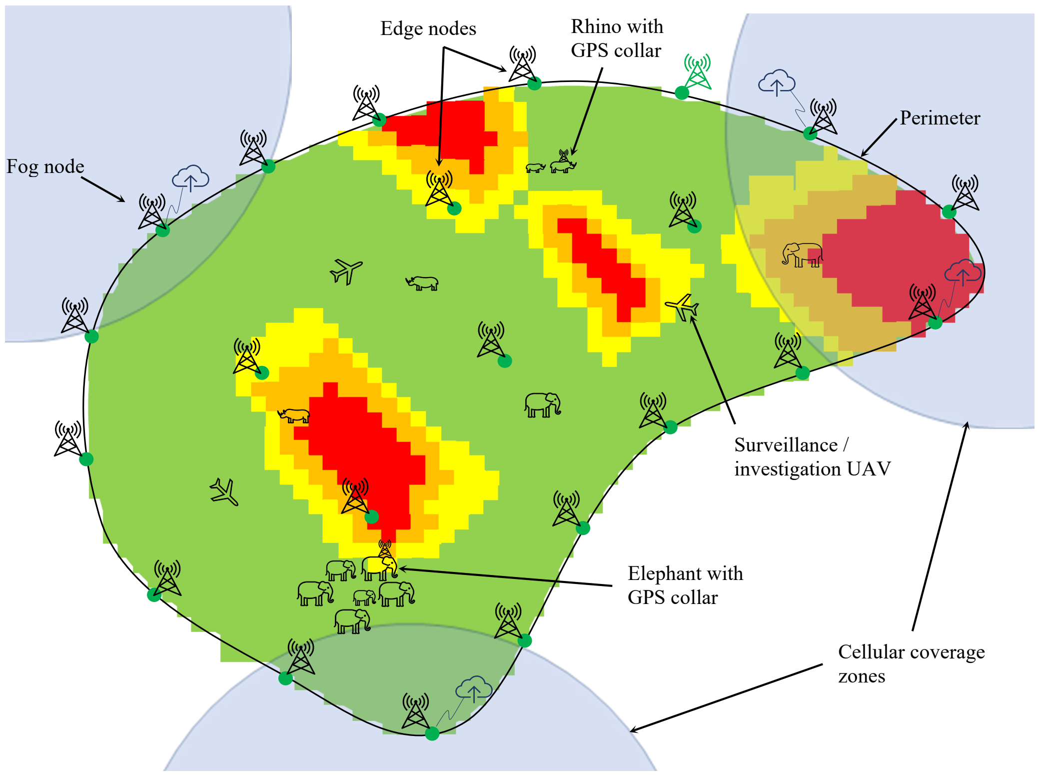


Fig. 20 Phase-C of a Notional Anti-Poaching System Showing a Heat Map of High Probability Zones for Elephant, Rhino, and/or Human Activity

B. Scaling of Fog and Edge Nodes with Simulation

The basic concept for scaling using Fog nodes that interface to Edge mesh nodes is a standard method for scaling IoT sensor networks. The more challenging questions to be answered are how well a scaled network will perform in terms of detection. While this cannot be answered by Phase-A or Phase-B bench and field tests of single sensors or multi-modal multi-sensor Fog nodes, the characteristics of each sensor can be determined. Given characteristics such as range of detection, frequency bands of interest for acoustic, and spectral imaging (NIR and visible), the capabilities and limitations of each can be integrated into a wide area simulation.

Simulation is envisioned using MATLAB Simulink and ROS Gazebo as described in Ref. [25, 26] such that game reserves of interest in South Africa such as Coleridge, Madikwe, and Rietvlei can be modeled. The basic numbers and behaviors of animals can then be simulated (as random walks between food, water, and boundaries) along with scenarios for human intrusion as well as expected human activity.

A scaled-out view of Rietvlei game park in Fig. 21 provides a reference for how the current Cloud-to-Fog-to-Edge sensor network architecture evaluated in this paper can provide coverage with cellular uplink to game wardens for faster response to incidents. The coverage is based upon the 1 km (measured) line-of-sight Zigbee/XBee range for Edge nodes in a mesh along with typical cellular availability (based on coverage maps for S. Africa cellular services).

Candidate sensors to be used in simulation scaling analysis will be stimulated by reactive agents in Simulink-Gazebo analysis as follows:

- Simulated elephants and rhinos with behavior based upon food, water, and other attractors and repulsive events or objects can be incorporated as reactive agents as described by Corke in Ref. [26].
- Simulated poacher activities and scenarios such as illegal entry into a park can be scripted for testing.
- Fog nodes to drive simulated heat map view of a virtual Rietvlei game park.
- Simulated flight of fixed wing drones with 360-degree FoV cameras for incident response, rather than satellite monitoring, for spatial awareness, but only when the heat map indicates a potential issue by location.
- Edge node cameras – to simulate detection of animals and vehicles at various locations over time at ranges characteristic of the cameras for objects of interest.
- Edge node microphones – to simulate detection of vehicles, humans, and animals at close range.

- Edge node geophones – to simulate vehicle traffic in unexpected areas and the presence of animals.

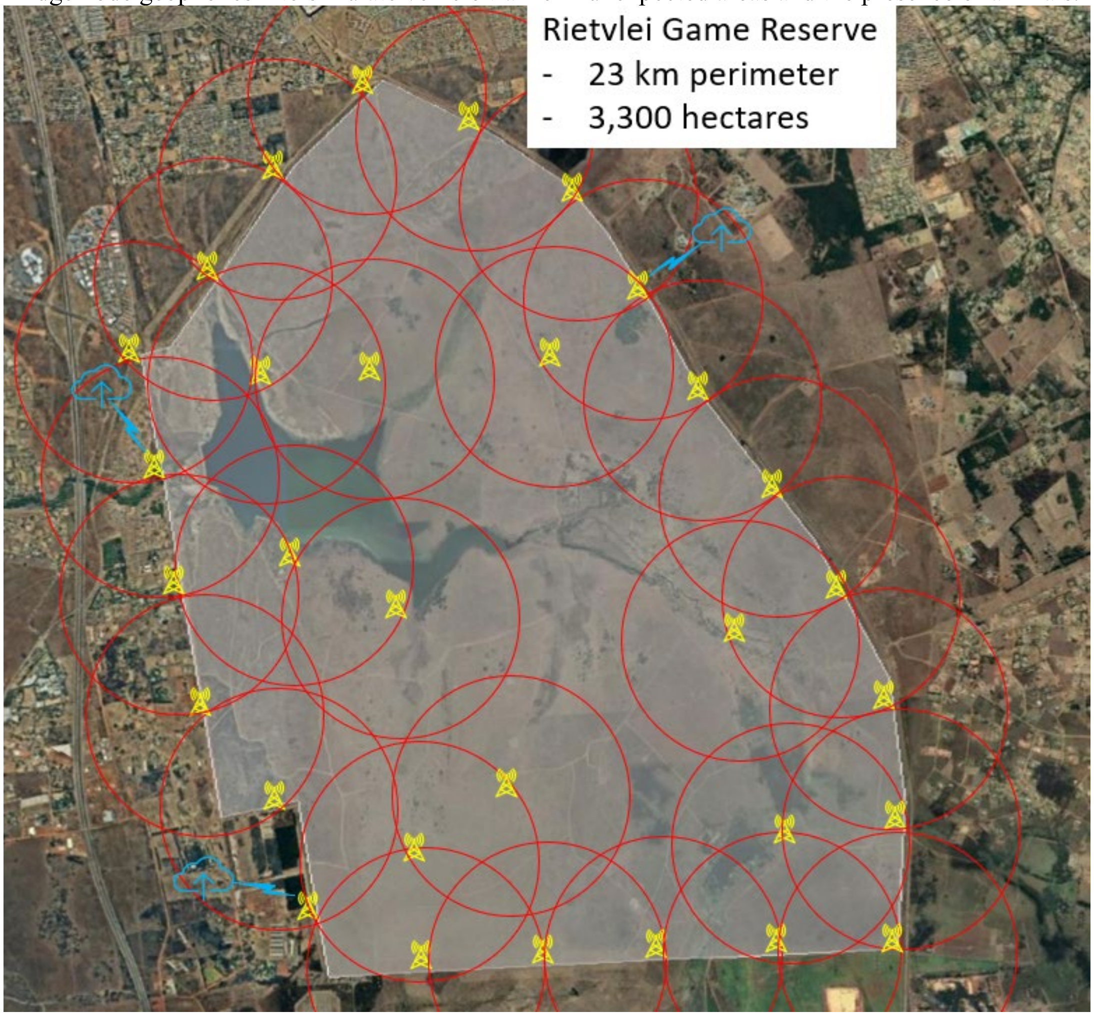


Fig. 21 Cloud-Fog-Edge Mesh Coverage Example at the Rietvlei Game Reserve

C. Use of Drones to Respond to Heat Map Potential Incidents

Since the project's inception the use of unmanned aircraft has been seen as viable tools in the fight against poaching. With satellite imagery being ruled out as a practical solution for continued game reserve surveillance, a greater emphasis will be placed on the use of UAVs for Phase-C. The use cases under consideration for drones are surveillance and investigation. The mission of a surveillance UAV will be large area coverage where the goal would be to create a big picture view of where animals are and to detect human activity. The investigation UAV, on the other hand, would launch on cue from the sensor network to investigate suspected human presence. Both missions would use high resolution visible and infrared cameras as the primary instruments onboard.

Compared to satellite imagery, the spatial resolution from a UAV is much smaller, and attempting to obtain a complete survey of a game reserve daily would not be feasible. A UAV would thus need to conduct surveys using optimized search patterns, informed by probabilities of animal locations and human activity hot spots. The areas surrounding watering holes, for example, would have a high probability of elephant presence. Hot spots for human activity would be near roadways near reserve fences. Fig. 20 is a notional view of hot spots where a surveillance aircraft may spend more of its time aloft. It has been suggested in the literature that there is a need for optimized surveying patterns other than line transects as noted in Ref. [27].

VIII.Conclusion

The goal of these experiments is mostly to practice data gathering in California at the CSU farm prior to making a trip to South Africa and to investigate methods of information and sensor fusion that will provide the best overall situation awareness for game preserve managers to manage Elephants, Rhinos, and interaction with people in a large area. Field testing of the geophone, one of the sensors that is most challenging in terms of deployment, has been completed and lessons learned have been incorporated into future planning. The overall SSIF architecture has been validated based upon field trials and bench tests of each proposed sensor assembly and integration into a Cloud-to-Fog-to-Edge sensor network. Further investigation is required to determine the efficiency of this SSIF design for scaling to the size of typical South African game parks (e.g., Rietvlei) and on-site testing of individual Fog node and Edge nodes is planned for summer 2024. The combined field trials, bench testing, and planned simulation scaling will ensure that the research team is ready to complete effective field trials on site in South Africa.

Acknowledgments

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