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TRANSPORTATION RESEARCH BOARD

Protection Detection: Making Roads Safe for Drivers and Wildlife

November 18, 2020

@NASEMTRB
#TRBwebinar

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#TRBwebinar

Learning Objectives

1. Identify hardware that detects and classifies animals along roads
2. Determine when Roadside Animal Detection Systems (RADs) make economic sense
3. Compare RAD approach with more conventional wildlife fencing and crossing structures

Roadside Animal Detection Systems & Artificial Intelligence

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Acknowledgements

TRB staff: Elaine Ferrell

Funding: USDOT Federal Highway Administration

AEP70 (Co-chairs Martin Palmer & Daniel Smith)

Fellow presenters: Nova Simpson, Hao Xu, Andy Alden

1. What are "Roadside Animal Detection Systems"?

Roadside: Can be associated with wildlife crosswalks, or in adjacent landscape, parallel to road

Animal: Typically thought of as for large, wild ungulates (deer, elk), but could be used for domestic animals, or smaller non-ungulates

Detection: Machine response triggered by animal presence

System: Ideally, detector(s) are associated with a device that signals drivers and more rarely the detected animal(s)

A lot of borrowing from vehicle-side technologies

Requirements and practice of object/animal detection

Rapid
Accurate
Flexible (across environments)
Generalizable (among species)

Rapid

- Vehicle-side – <<1 sec at highway speeds to allow stopping (reaction + braking) distance of 100 m
- Roadside – depends on animal type and speed, vehicle speed, distance to roadway of detection
  - For a sprinting animal, travels 40 feet per second
  - Vehicles may need 3-4 seconds to react and stop
  - Ideally, the animal should be detected in <1 second and far enough from the roadside or vehicle to allow driver warning

Accurate

Two types of avoidable conditions:

1) False negative – animal is present, system does not detect/warn
2) False positive – no animal is present, system falsely warns

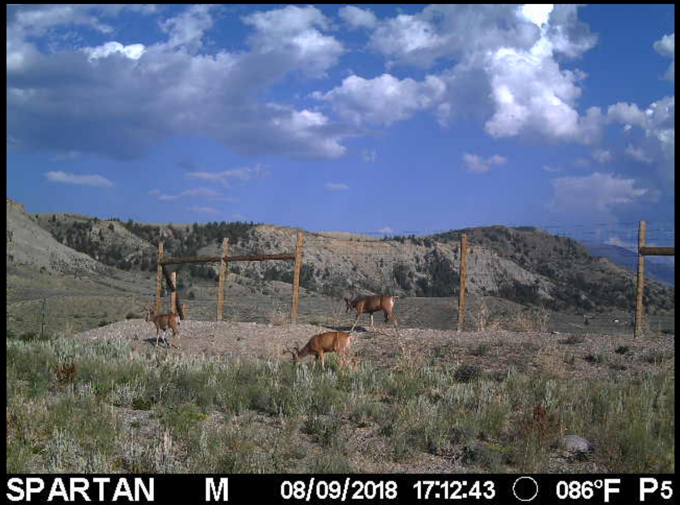
What is the desired %accuracy for each? #1 bad for safety, #1 & 2 bad for public buy-in and trust

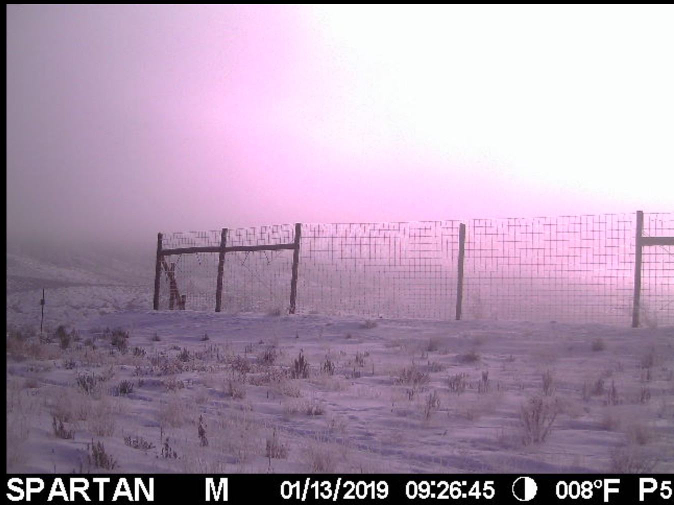
Flexible/hardened

Climate – outdoor ROW temperatures likely between <-20 F and +120 F, ranges of 100 F possible annually

humidity can likewise range widely, <10% to 100%

Background – can tolerate changes in background conditions





Generalizable

Species – its desirable to develop tools that are useful beyond deer/ungulates

Species groups – it may not be necessary to discriminate based on species if larger groups meet goal

2. Specific Detectors/Sensors

Camera/video

LiDAR

Thermal

Radar

Buried cable

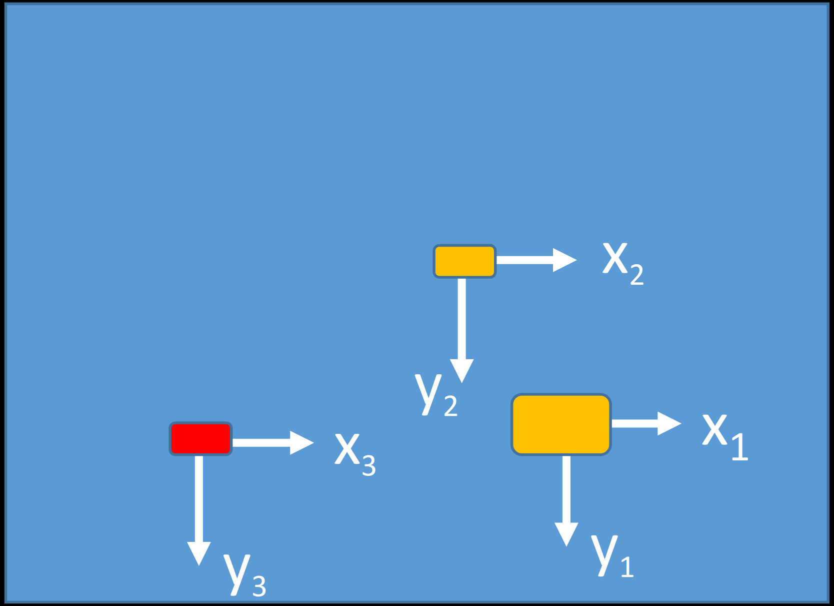
The first 4 may require, or benefit from AI help

Thermal

Relies on heat signature, can be combined with AI

Sensitivity and resolution depends on physical sensor, which can drive price

Position in frame, size of object



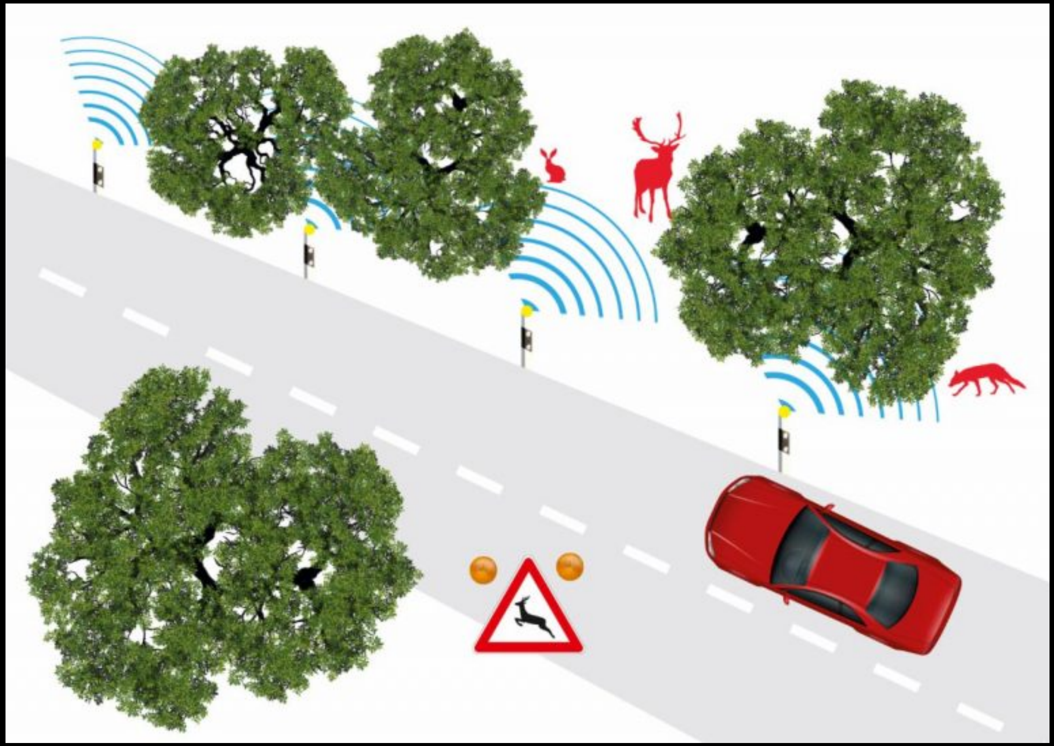
Radar

Doppler effect, can be combined with AI

Sensitivity and resolution depends on physical sensor, which can drive price

All-weather, v. long-distance

NavTech



Temcom

Still imagery

Combine with Artificial Intelligence/Machine Learning

Could be combined with passive feed

Total time for object detection, image capture, image processing and object classification must be <1 sec

Object trajectory mapping possible

Video/CCTV

Combine with Artificial Intelligence/Machine Learning

Based on passive feed

Total time for object detection, frame(s) capture, processing and object classification must be <1 sec

Object trajectory mapping possible

3. AI/ML tools

Object detection (boundary box around object of interest)

Object classification (what is in the box, is it of interest?)

iNaturalist “Seek” (https://www.inaturalist.org/pages/seek_app)

MS MegaDetector (https://github.com/microsoft/CameraTraps/blob/master/megadetector.md)

MLWIC (**Machine Learning for Wildlife Image Classification in R)**

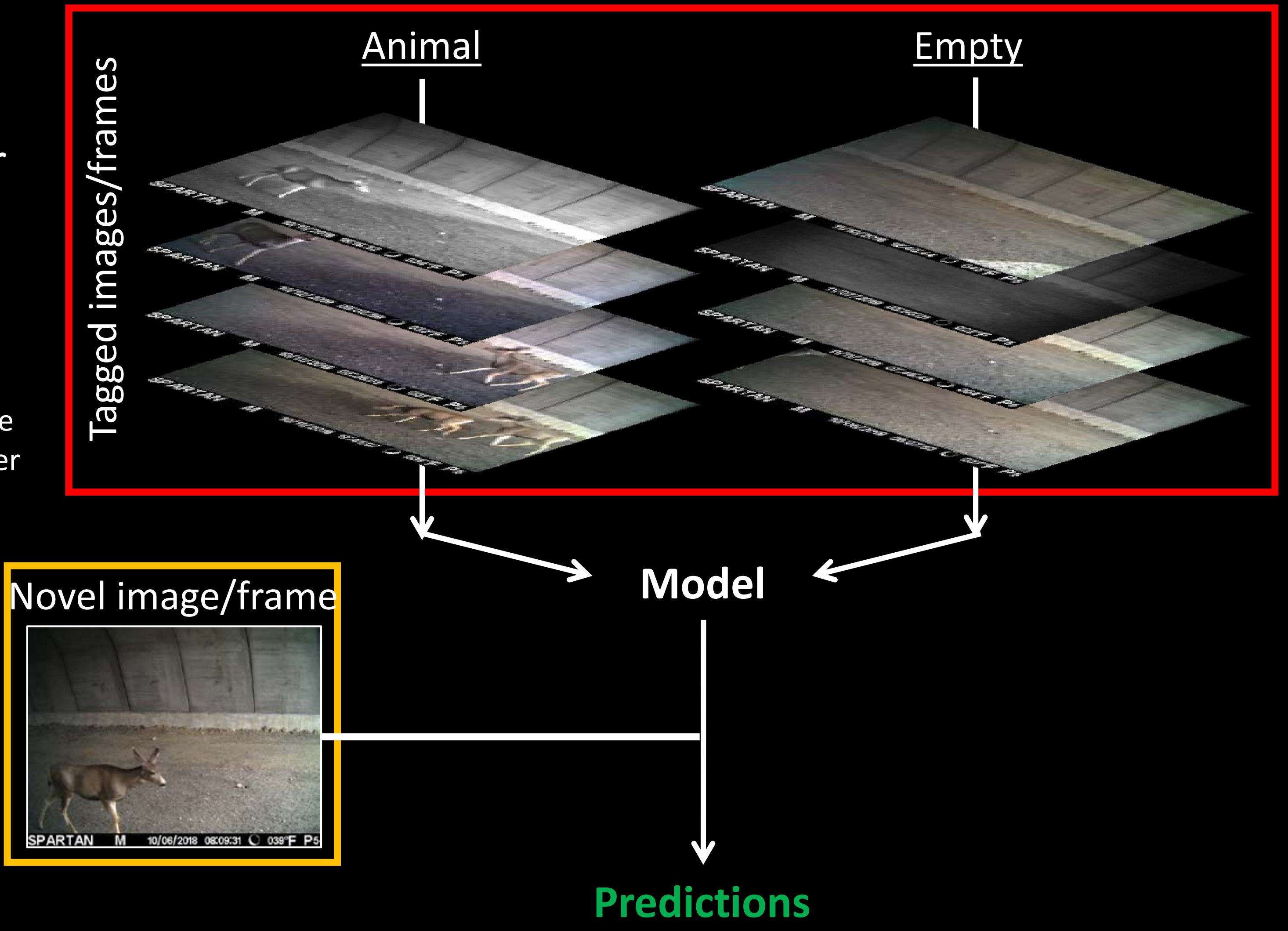
ResNET (“residual” NN) processes

Various custom YOLO (You Only Look Once) and CNN (Convolutional Neural Network) solutions, such as Fast RCNN (Region CNN)

Machine learning

- Machine learning
  - Increasingly used for computer vision applications
  - Pattern recognition, object detection/classification
- 1: Train a model
  - A: Train model
  - B: Test model
  - Training and testing data
- 2: Generate predictions
  - Input: an image
  - Output: A classification, an image, a location, etc.

Do both of these many times, over and over again



3 tools for automated classification

Microsoft's megaDetector

- Based on FASTER R-CNN architecture

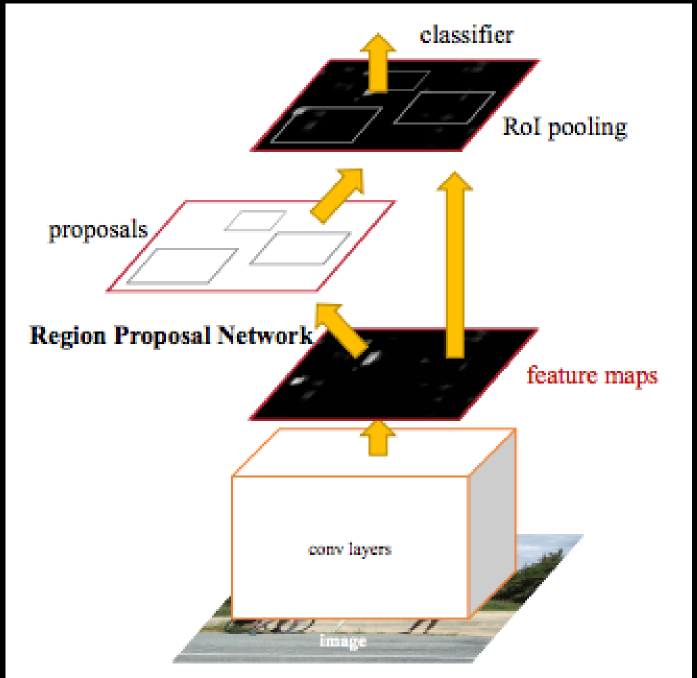
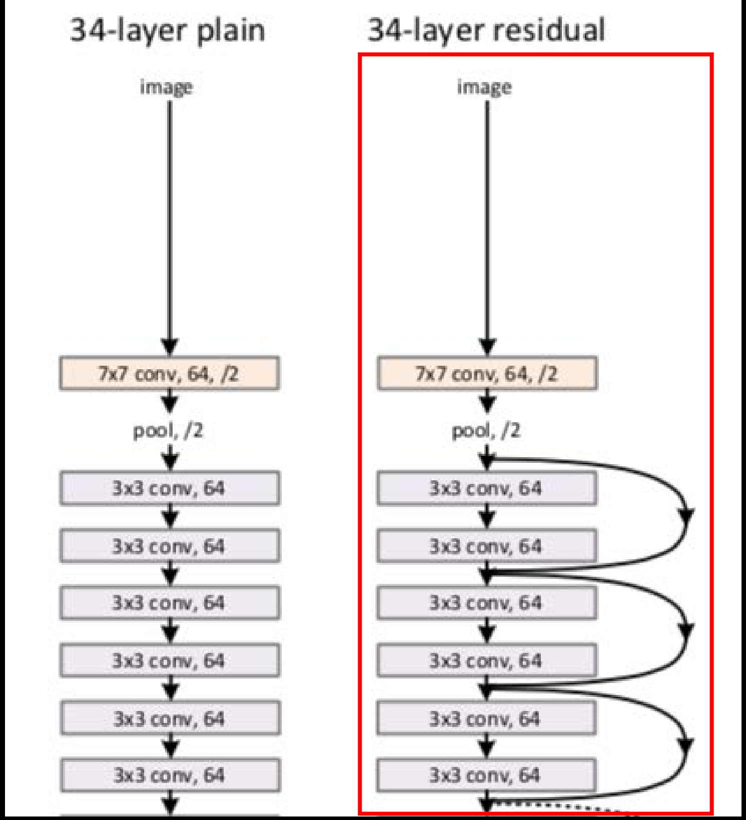


Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the 'attention' of this unified network.

Ren et al (2015)

MLWIC (Tabak et al 2018)

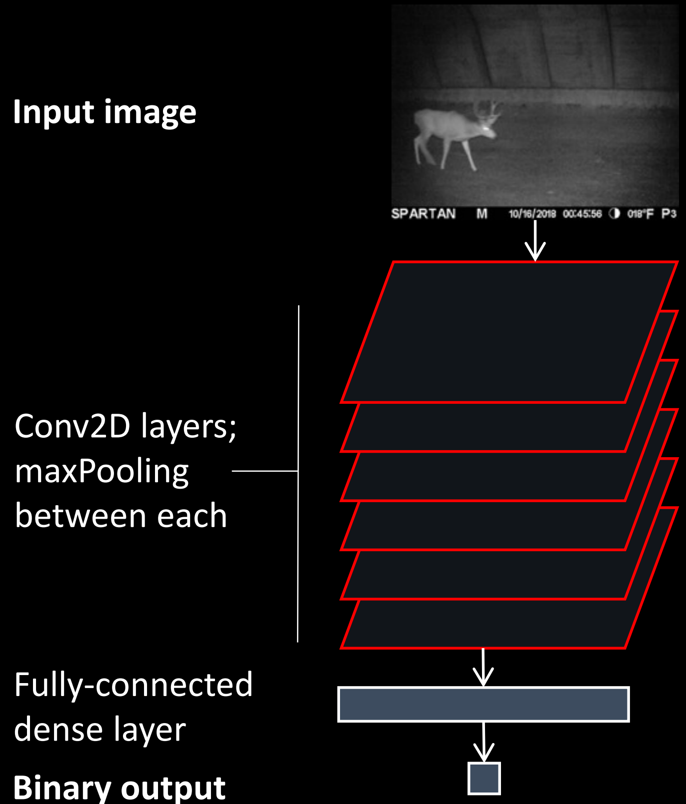
- Based on ResNet-18 architecture



He et al (2016)

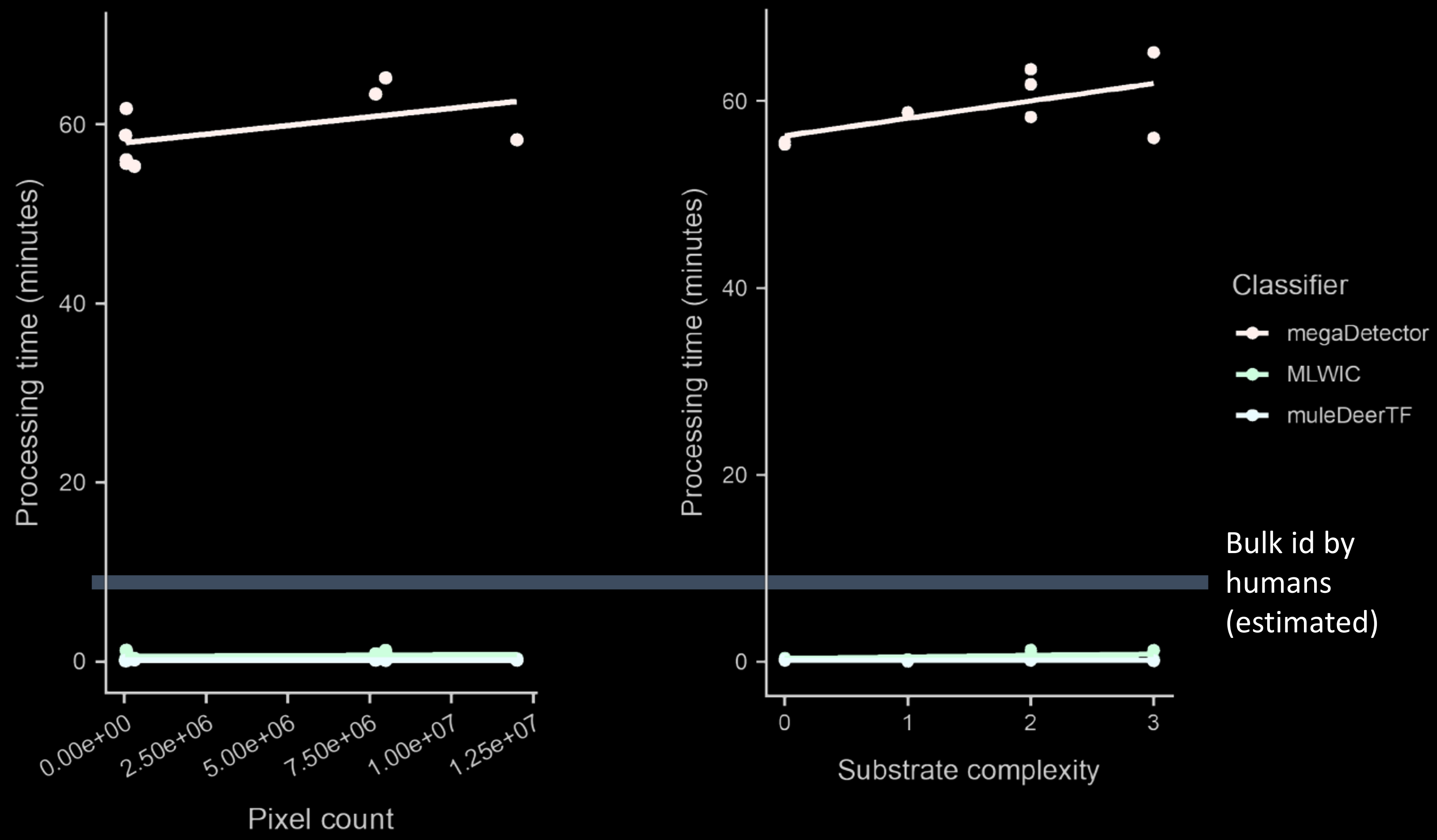
Custom mule deer detector

- Simple, 6-layer CNN built in tensorflow::keras API



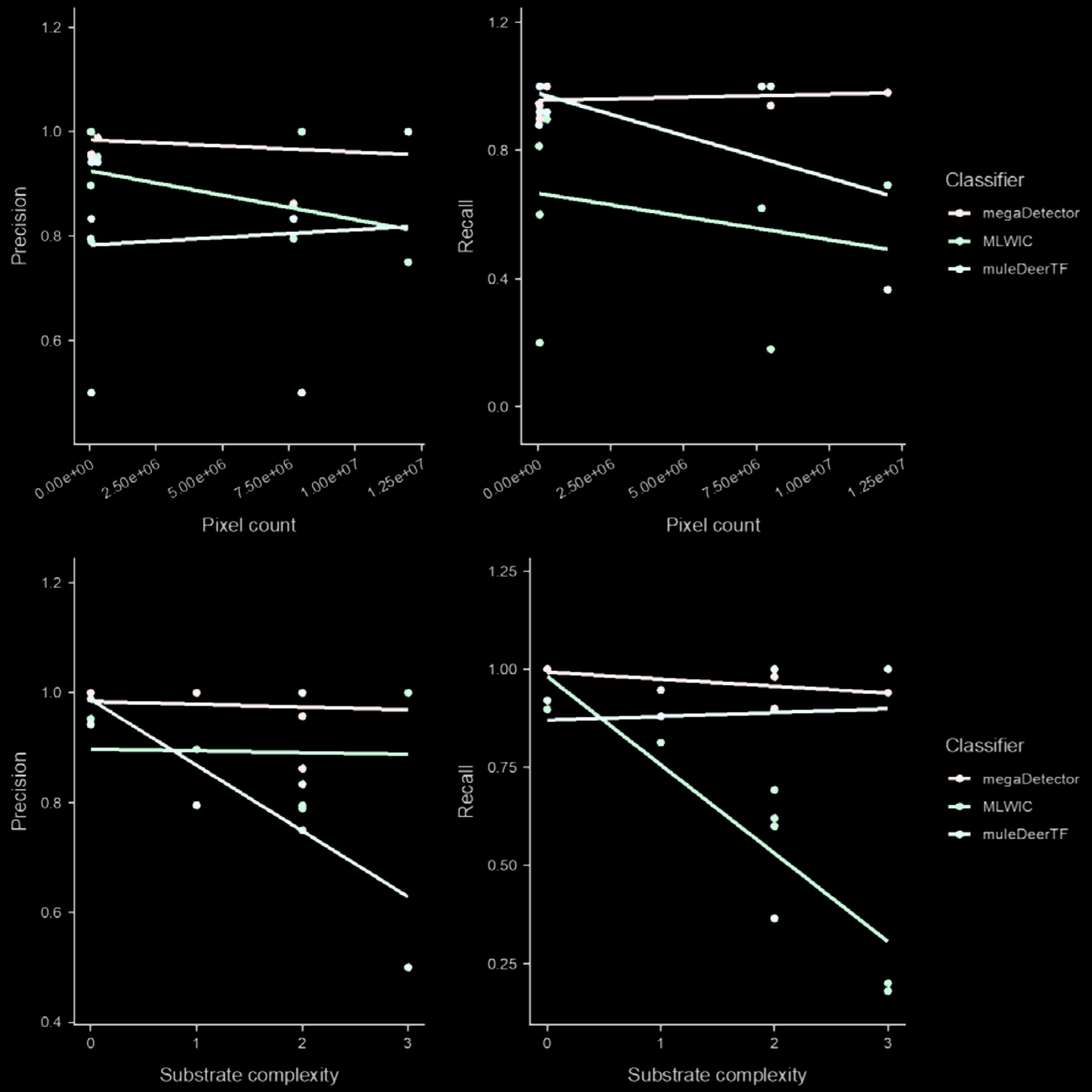
Results (speed)

- 8 sets of N = 100 images from highway-related camera trap projects
- Vantage points, camera models, and sensitivity settings:
  - Image size
    - Pixel count
  - Image setting
    - Substrate complexity



Results (accuracy)

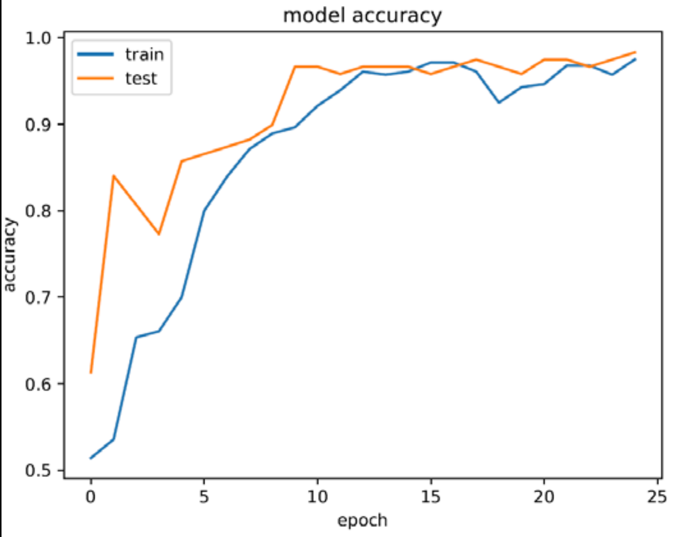
- In general, no significant effects of image size or complexity on accuracy.
  - Exception: MLWIC
    - Of images containing an animal, MLWIC tended to miss animals when the substrate was complex.
- Most reliable: megaDetector, across environments

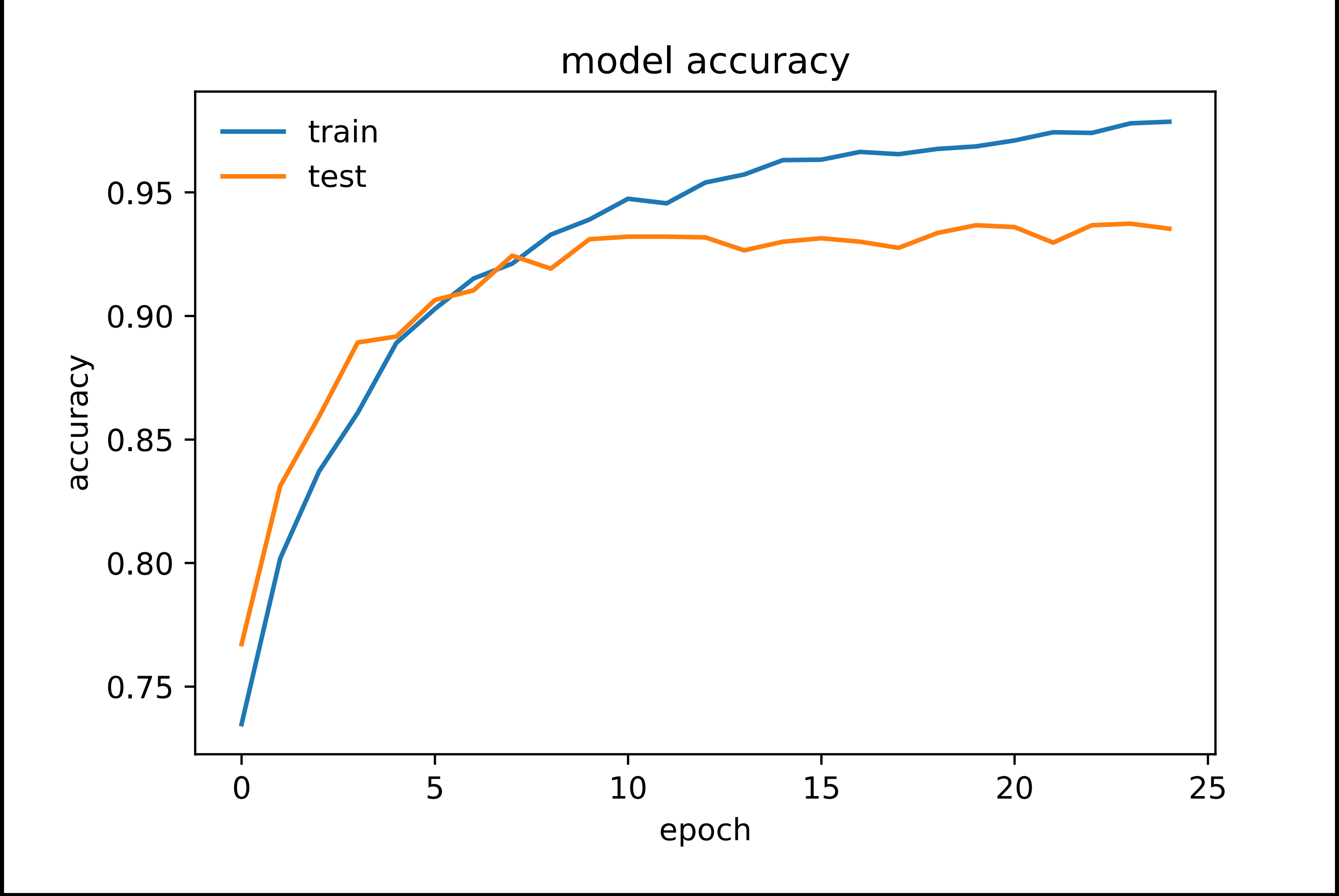


Custom automated deer identification

KERAS CNN, 25 epochs training; 25,000 images, 12 camera positions; species ID in 0.1 sec, 92% accuracy

New approach, 0.1 sec >95% accuracy





Effectiveness

AZ wildlife crosswalk combined with fence: >95% reduction in WVC and 100% reduction in human fatalities and injuries (Gagnon et al., 2019)

Suggests that similar response rates could be observed for pure RADS (no crosswalk/fence), depends on fast/accurate detection and positive driver response

Fencing/wildlife crossings – up to 80% reduction in WVC, with higher and lower rates (Rytwinski et al., 2016)

Costs

Range of technologies, costs, and readiness for roadside animal detection systems. Costs are for detection systems only, not the corresponding driver warning signs. (Including information from Drs. Hao Xu and Andrew Alden, University of Nevada Reno and Virginia Tech Transportation Institute, respectively)

Technology	Proven effectiveness	Up-front cost (cost/length)	Maintenance requirements	Readiness
Video feed	Limited	$100,000/mile	$$, maintain station	Research-grade
Buried cable	Useful for deer or larger	$100,000/mile	$$, maintain station	Research-grade
LiDAR	Useful for deer or larger	$30,000/100 m	$$, maintain station	Research-grade
Radar	Useful for larger animals	$100,000/mile	$$, maintain station	Limited field-implemented
Thermal camera	Useful for medium to large mammals	$30,000/100 m	$$, maintain station	Field-implemented

Bottom line: competitive with fencing/crossing pricing

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Roadside LiDAR Sensing
Roadside Animal Detection Systems (RADS)

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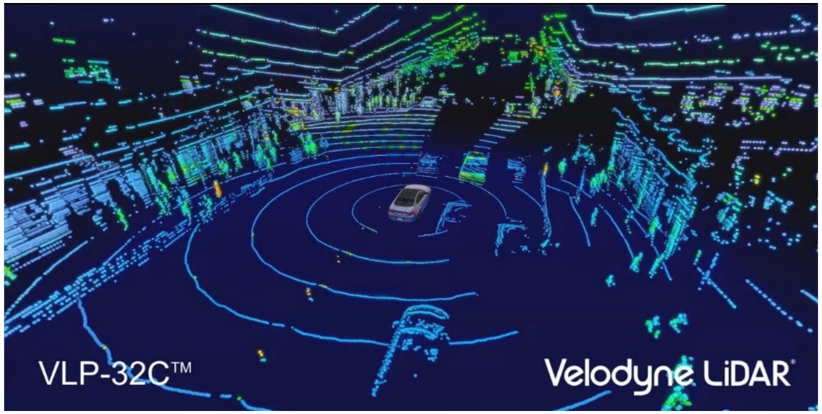
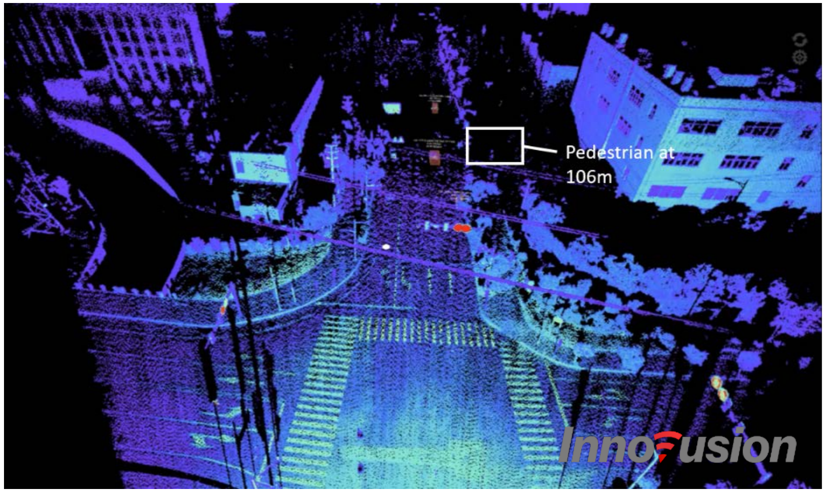
LiDAR Sensors “Migration” – Vehicles to Infrastructure

LiDAR for Detecting Wildlife Crossing

- High spatial accuracy
- Data geolocation for roadside or in-vehicle warning
- 360º coverage – road surface and roadside
- 3D cloud points require less computation
- One sensor for multimodal traffic data
  - volumes, speeds, crossing paths, conflicts and interactions
- Not influenced by light condition





LiDAR Sensors for Roadside Sensing

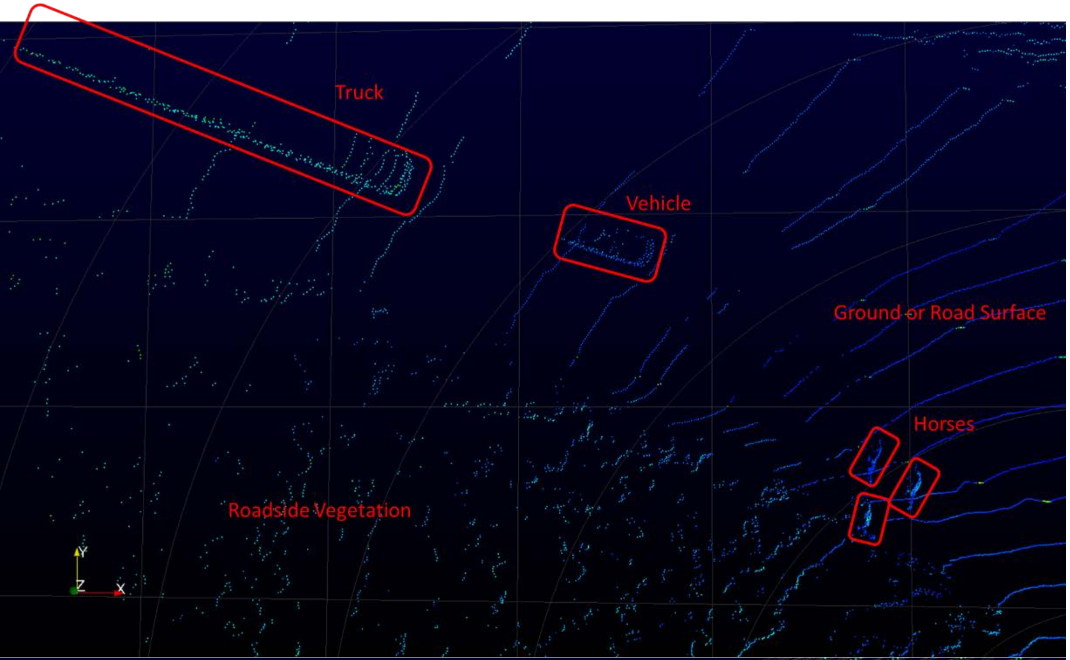
360-Degree LiDAR (Rotating LiDAR)

- Number of laser beams for rotating scan
- Vertical field of view (angle)
- Detection range – radius
- Price
- Installation location

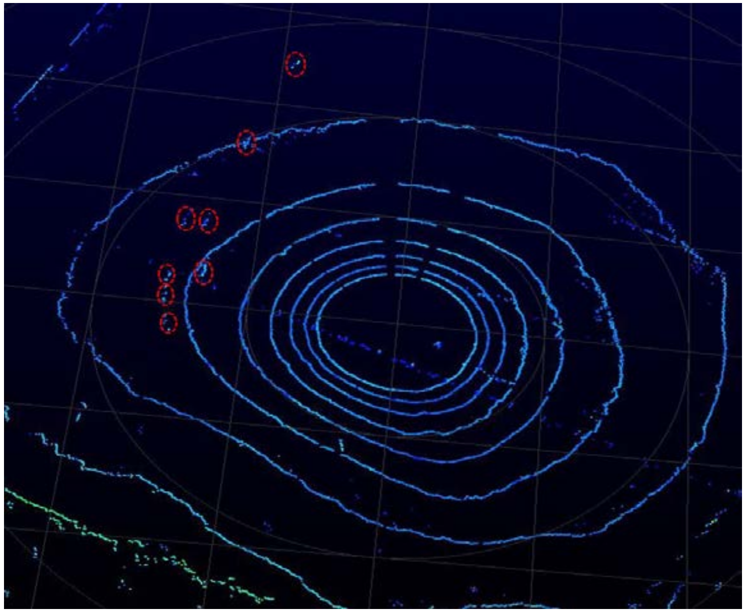
Non-Rotating LiDAR

- Equivalent number of laser beams
- Horizontal field of view (angle)
- Vertical field of view
- Detection distance
- Price
- Installation location

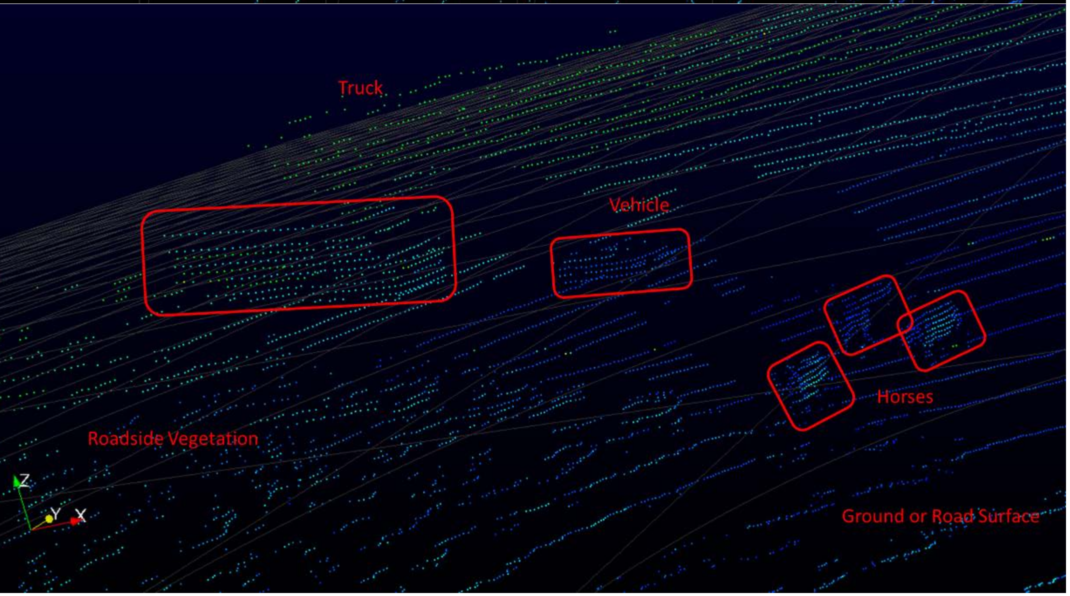
Raw LiDAR Data – 3D Points of Surfaces



Top-view of LiDAR Cloud Points – Traffic and Horses (32-line rotating LiDAR)

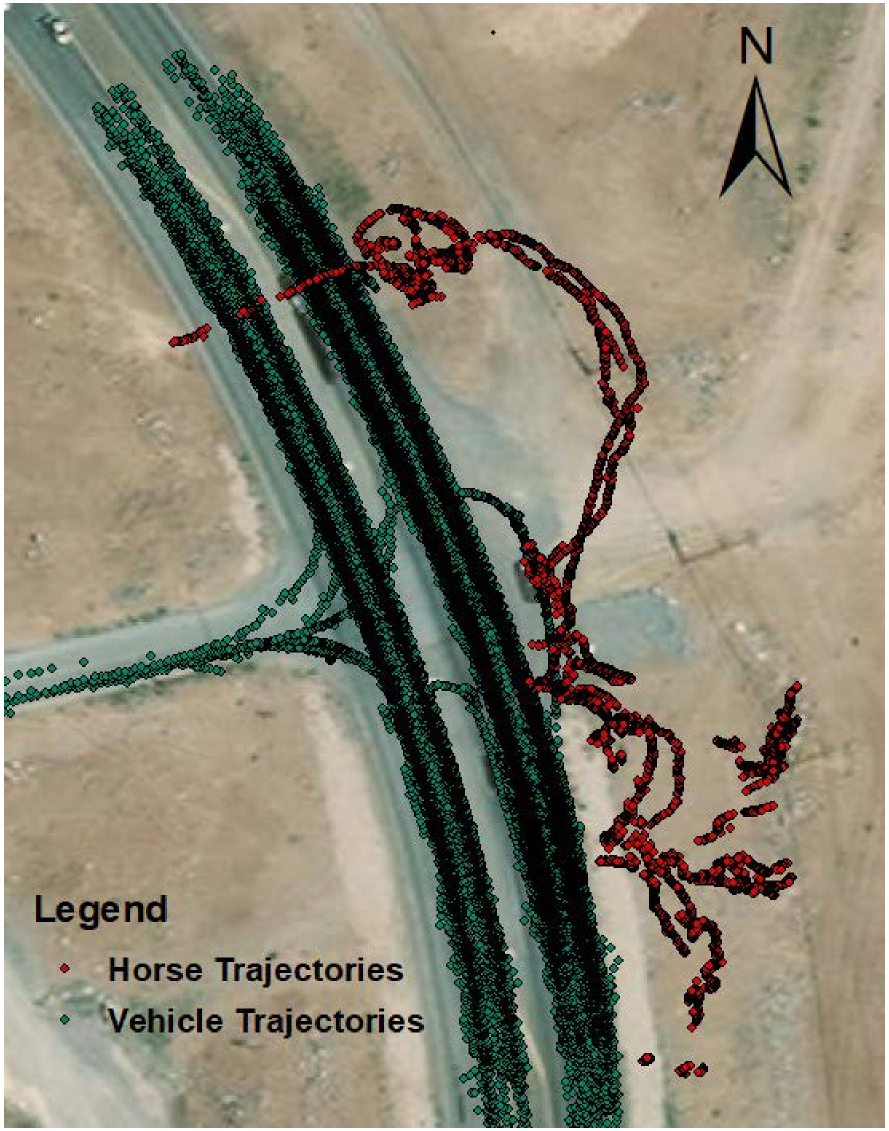


Top-view of LiDAR Cloud Points – Deer (16-line rotating LiDAR)



Side-view of LiDAR Cloud Points – Traffic and Horses (32-line rotating LiDAR)

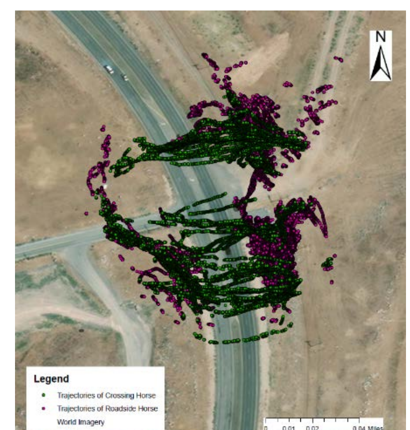
Georeferenced Vehicles and Horses Movement



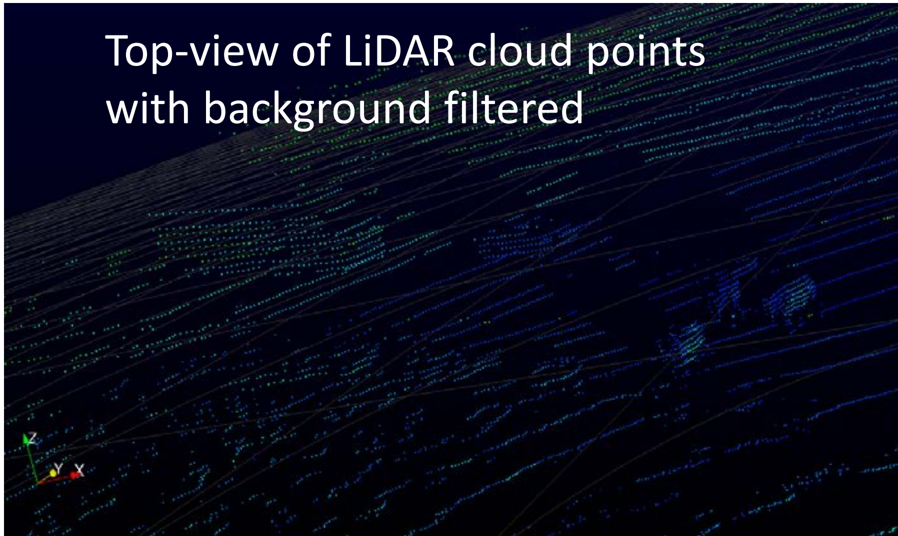
Roadside Signal

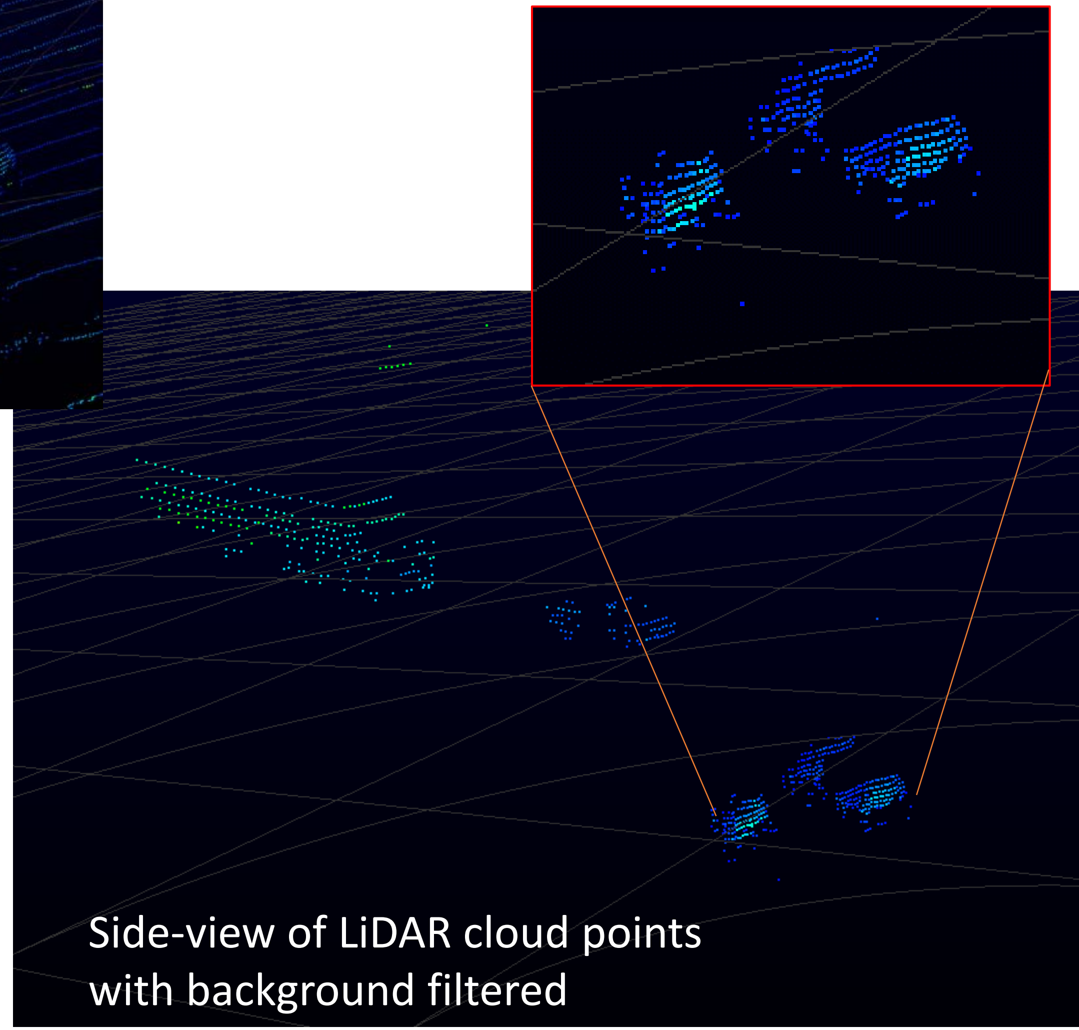
Connected and Autonomous Vehicle Messages

Offline GIS Analysis / Safety Evaluation



LiDAR Data Processing – Exclude Background





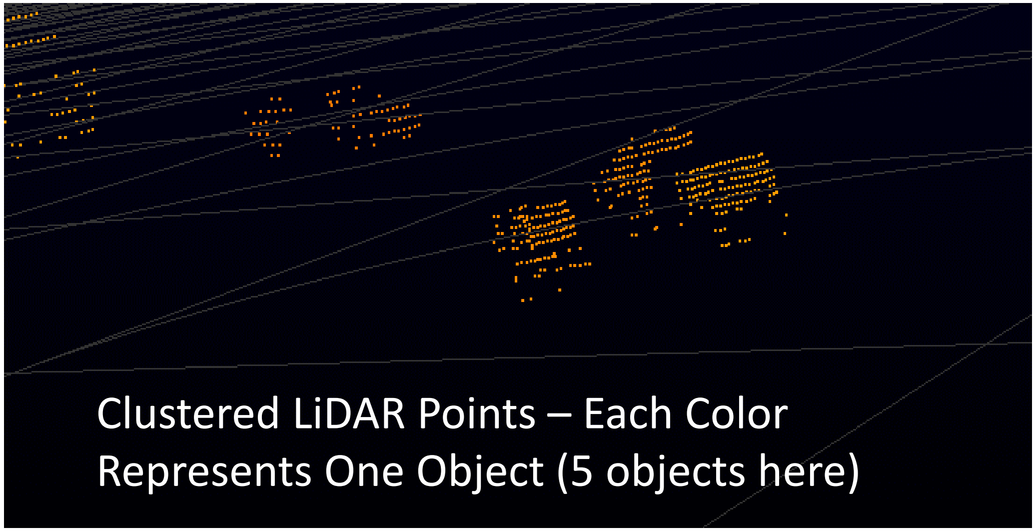
LiDAR Data Processing – Object Clustering & Classification

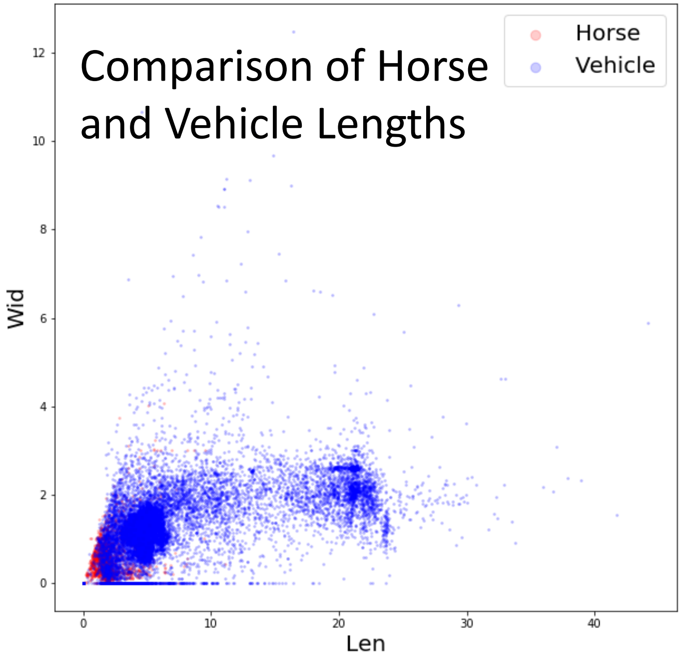
Machine learning algorithms:

- Convolutional neural network
- Random forest
- Deep neural nets
- Random Undersampling Boost
- Adaptive Boosting for Multiclass Classification

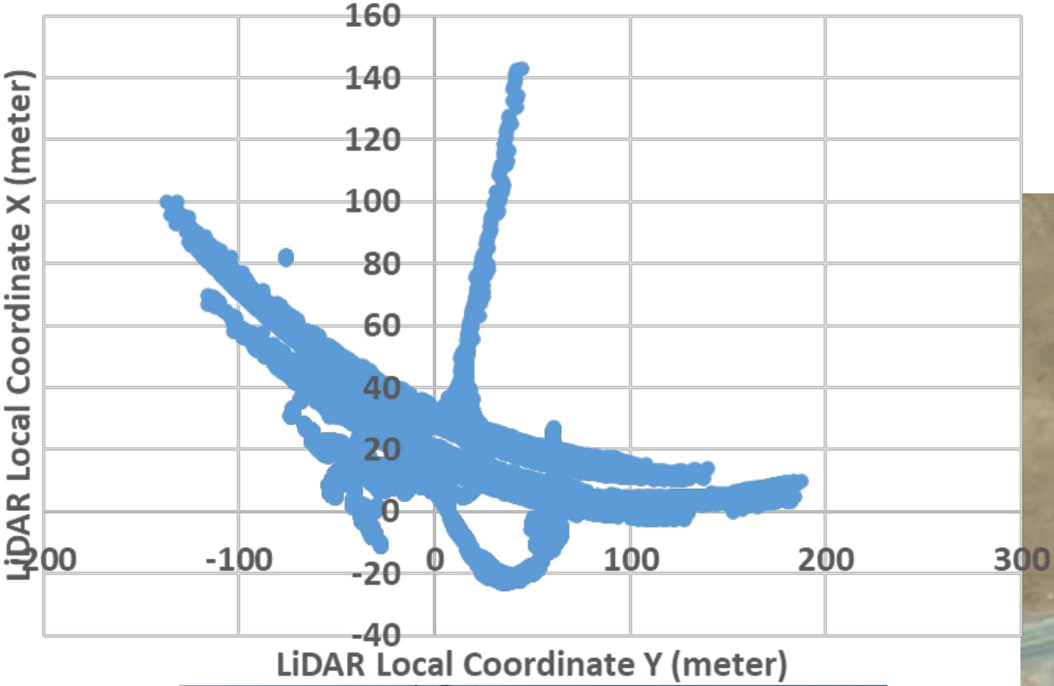
Object features

- Object length
- Height
- Width
- Distance to the sensor
- Direction
- Speed
- Road lanes/boundaries





LiDAR Data Processing – Object Tracking and Georeferencing



Influencing Factors on LiDAR Sensing

Inclement weather

- Rain and snow – LiDAR "see" as far as human eyes
- Blown dust – may generate LiDAR points like road users

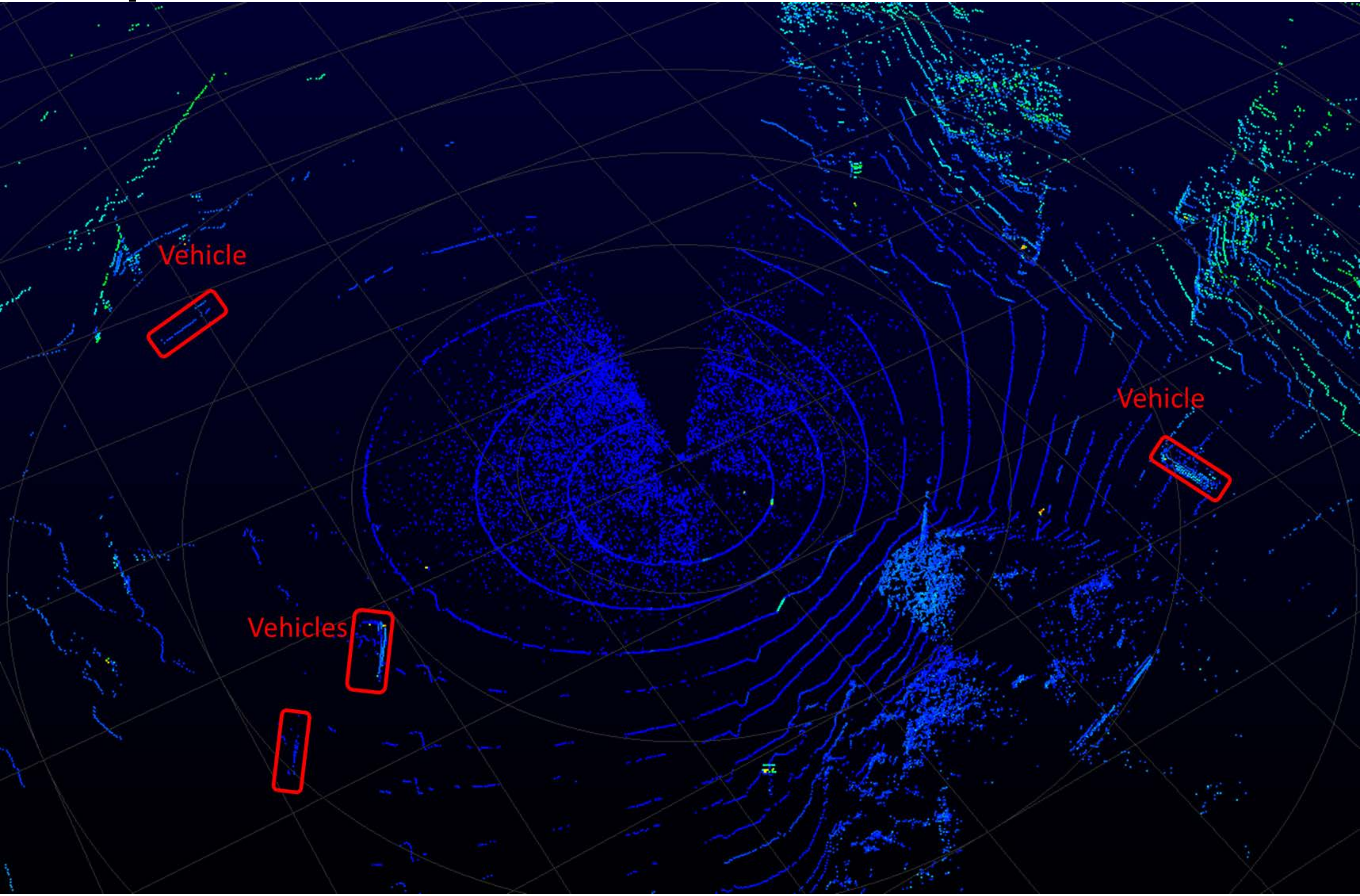
Occlusion

- Occlusion caused by traffic
- Occlusion caused by roadside obstacles – trees and rocks

Data processing methods and software

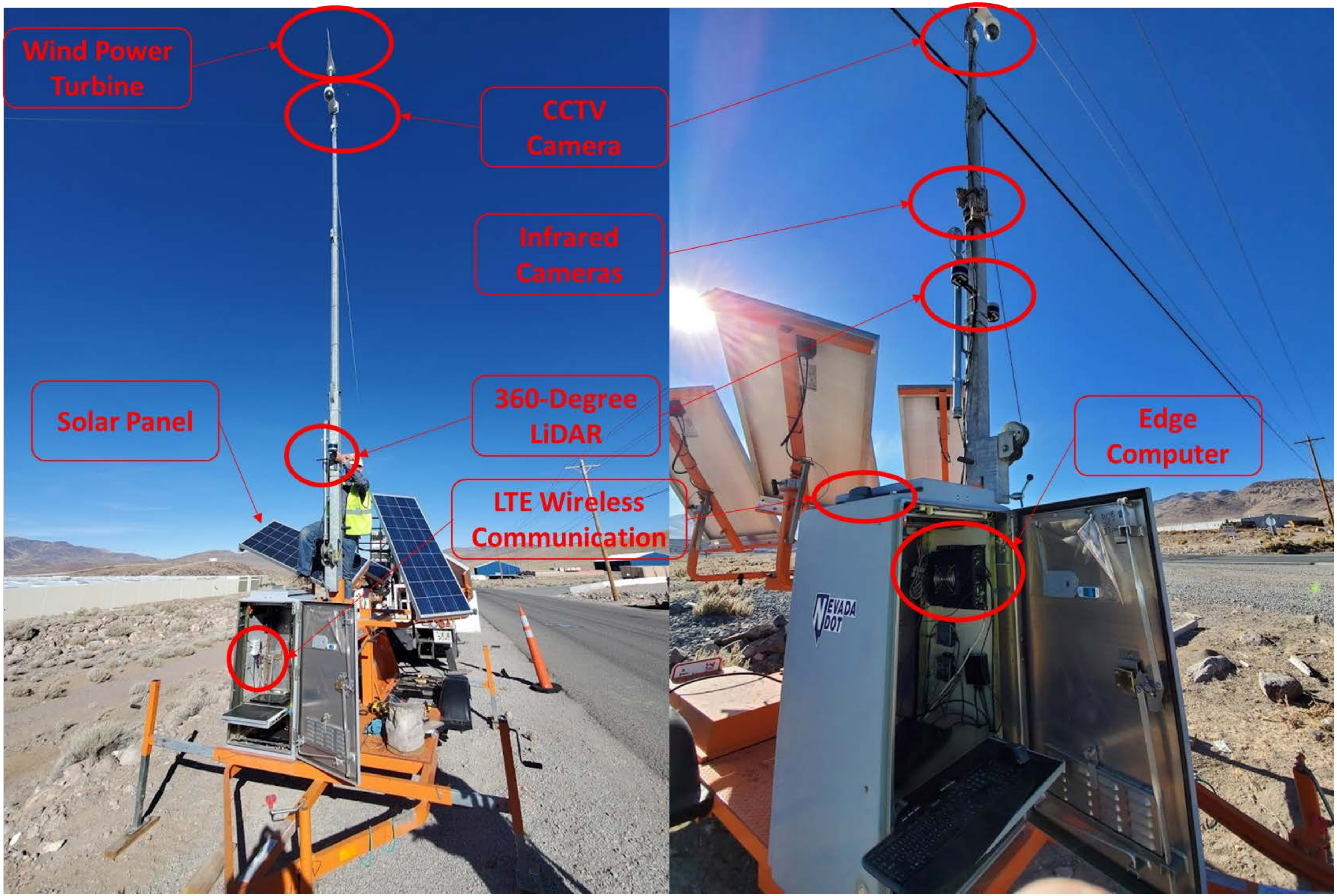
- Performance can often be determined by the software rather than sensors

Sample Snow Weather LiDAR Data



Sample Mis-Identification – Blown Dust

Platform and Related Devices



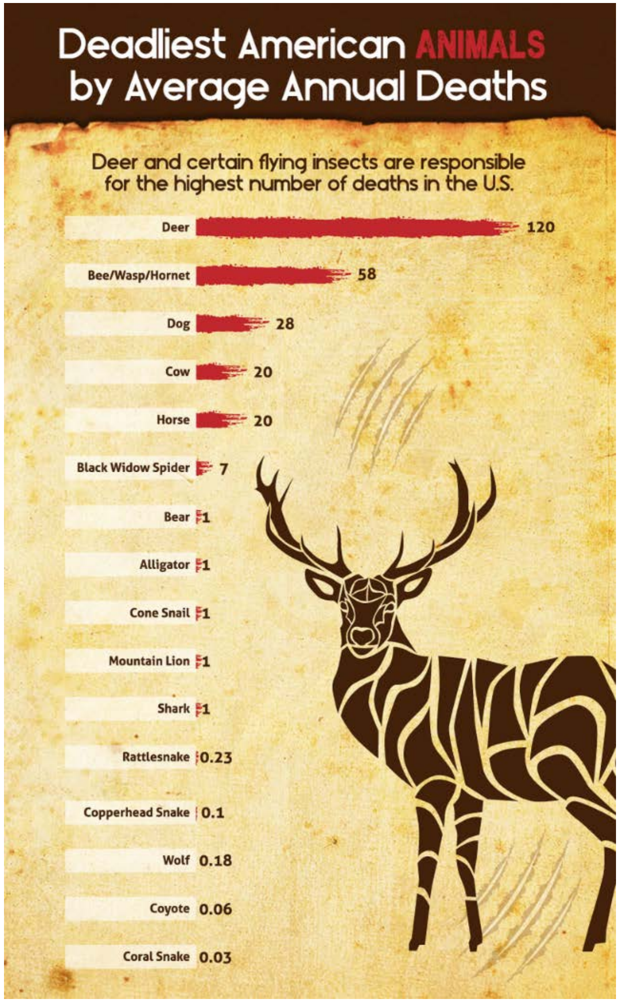
Buried Cable Systems for Roadside Animal Detection

Andy Alden
Virginia Tech Transportation Institute

Acknowledgments
Project Manager: Cristian Druta
Sponsor: VA Department of Transportation

Motivations & Research Focus

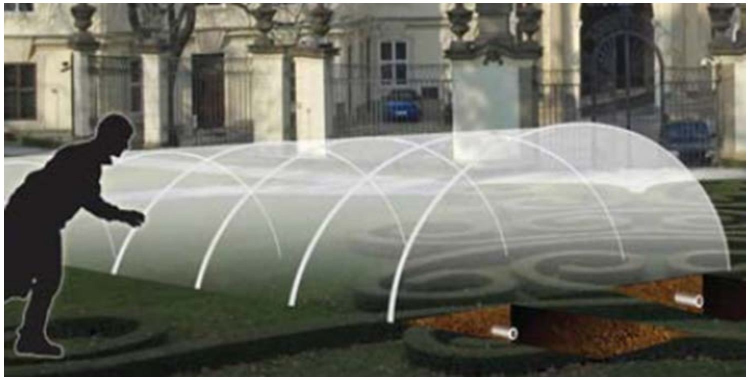
- The Problem
  - 1 million+ crashes yearly and increasing
  - $4 billion direct damage
  - ~150 human deaths
  - Ancillary costs
    - Incident management
    - Carcass collection/management/disposal
    - Disruption (e.g. congestion)
  - Ecological impact
  - Driver trauma
  - Conflict versus collision?
- New technologies as measures to address
  - Connected vehicle
  - Autonomous vehicle sensors
  - Roadside detection systems

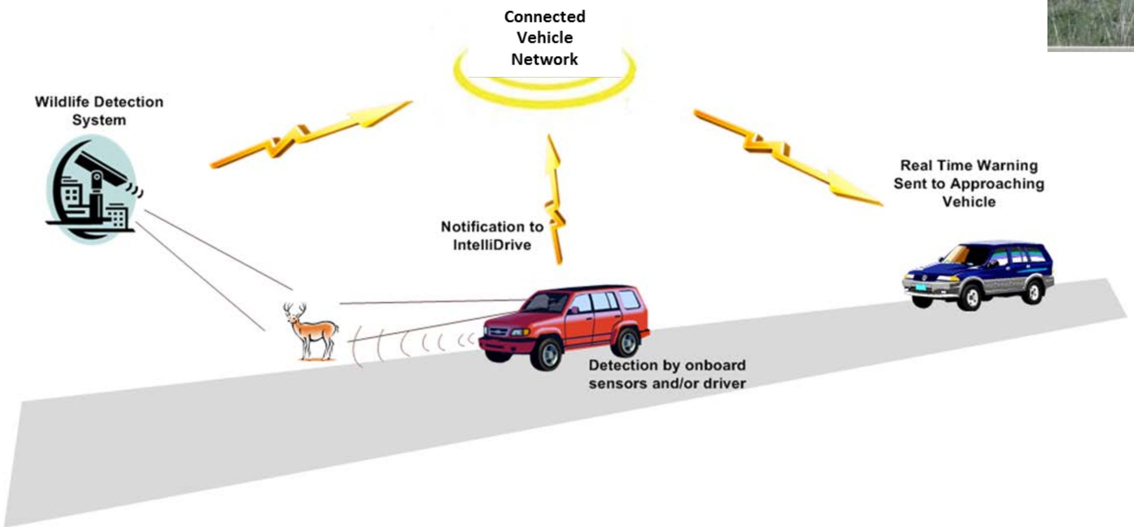


Source: wonder.cdc.gov

Buried Cable Detection Systems

- DOD development for perimeter security
- Two phases of work funded by VDOT
  - Phase 1 – System evaluation on the Virginia Smart Road
    - Observed 95% detection reliability
  - Phase 2 – System evaluation on Virginia public road
    - Tests completed Summer 2018
- Conflict threat communicated to approaching vehicles
  - Via roadside warning sign





Objective and Scope

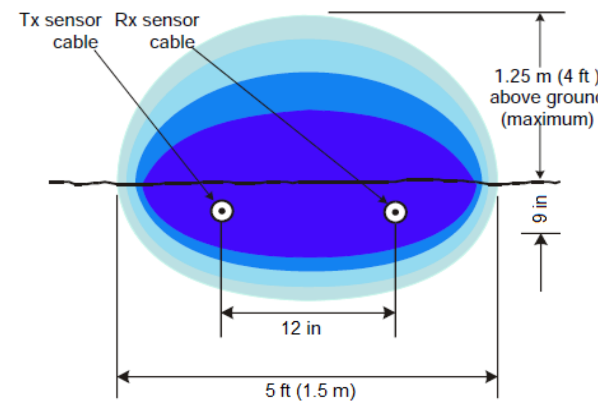
- Primary goals
  - Evaluate Omnitrax sensor (BCADS) system performance on public road
  - Identify and assess site-specific implementation issues
  - Evaluate the flashing warning sign
- Secondary goal
  - Assess various power and communication options

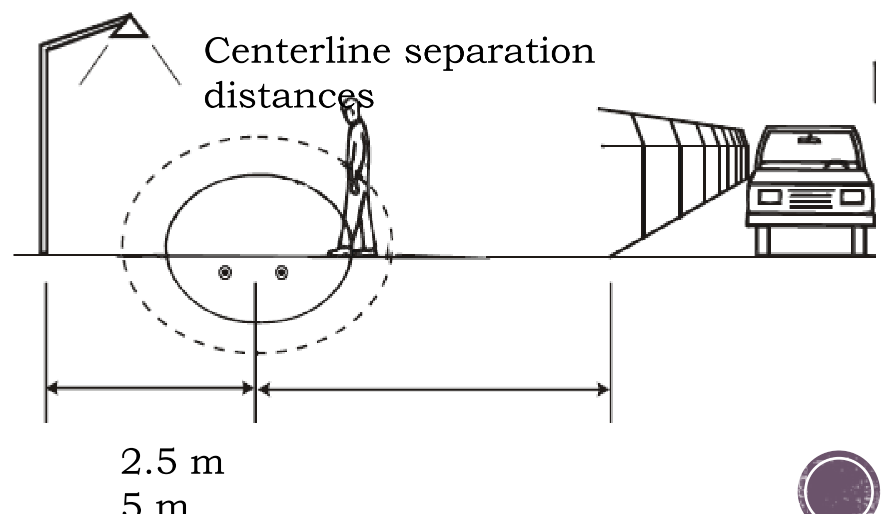
Installation Approach

– Location with ‘reliable’ population of large animals
– Supporting power and communication access
– Landowner cooperation
– VDOT Permit and VT MOU

Omnitrax Cable System Characteristics

- Ported (leaky) coaxial cable technology
- 120 m long cables run in one direction from the processor box
- Detection based on intruder's elec. conductivity, size, and speed (75 lb. triggers alarm)
- Cable sensing system can operate as standalone sensor or be remotely managed
- Mostly unaffected by vegetation, weather, vibration, blowing debris



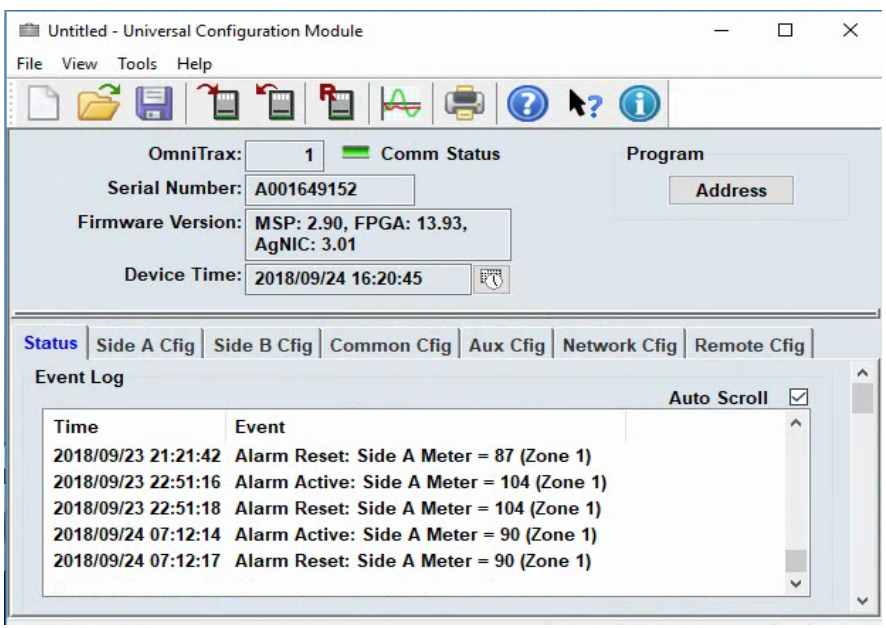


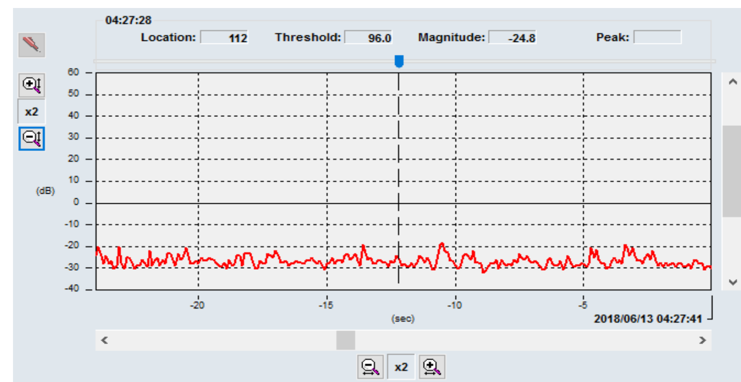
Installation Location

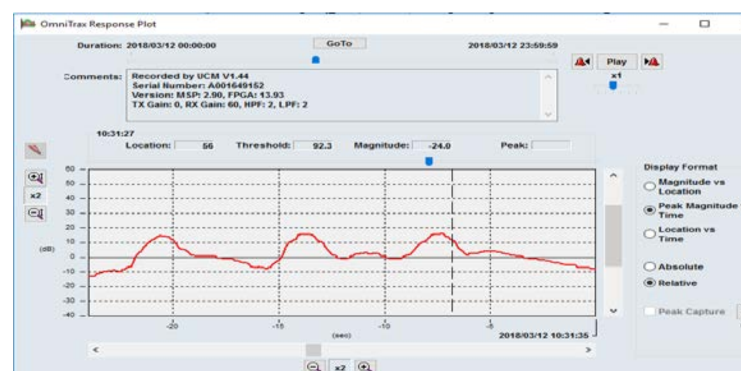
Cable Field Installation

System Setup

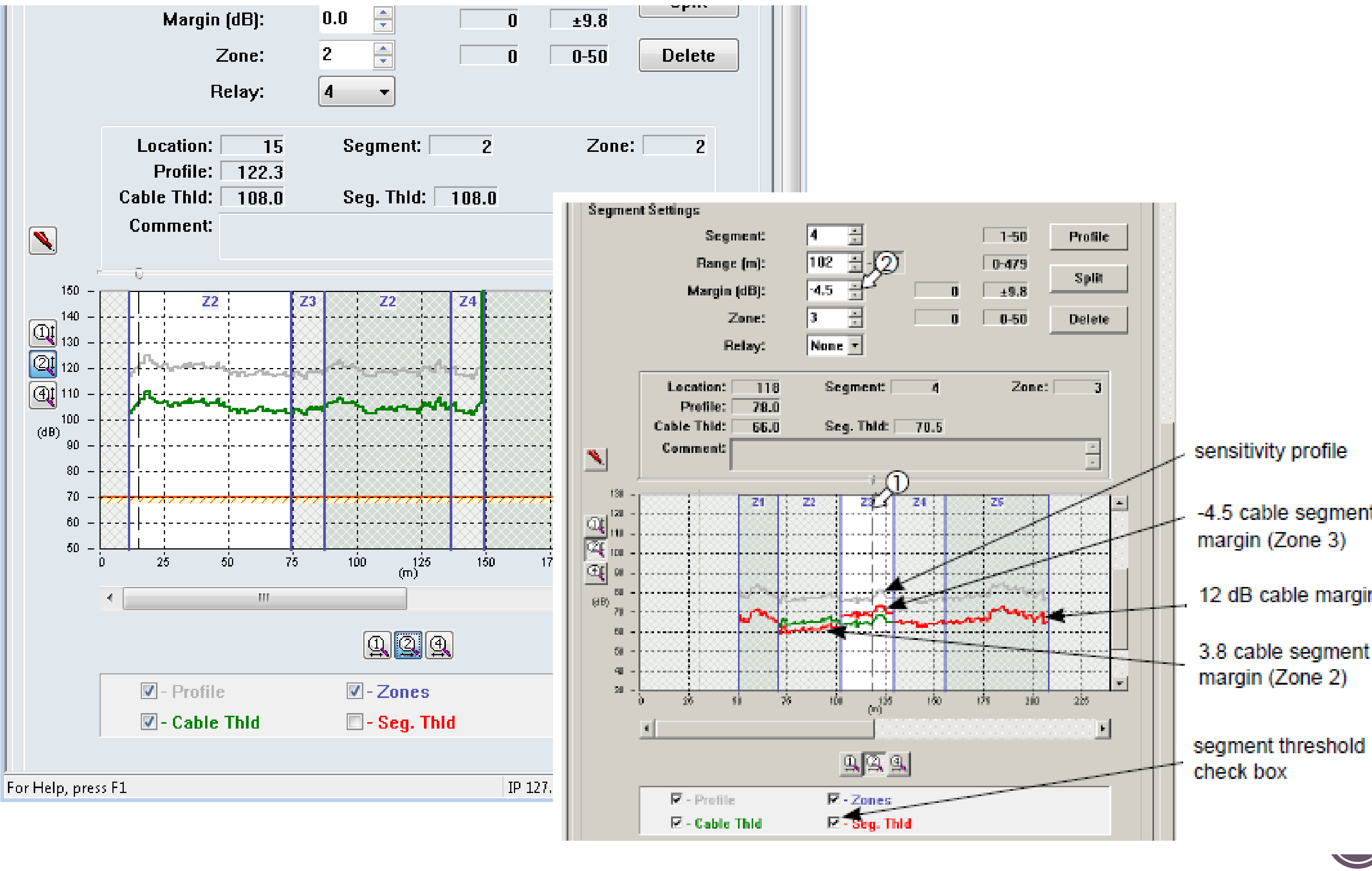
- OmniTrax Universal Configuration Module (UCM) software used for the calibration/setup procedure of the system (sensitivity profile)
- UCM software can be also used as a maintenance tool
- Network Manager (NM) software for remote control



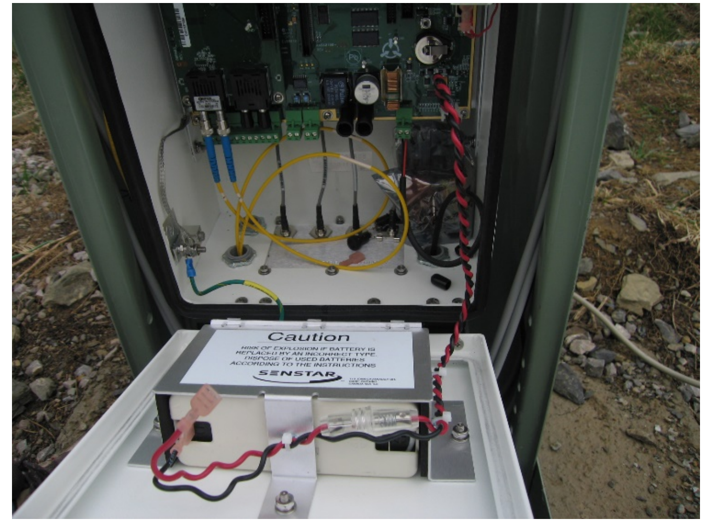




Cable System Calibration



Deer Crossing Flashing Sign

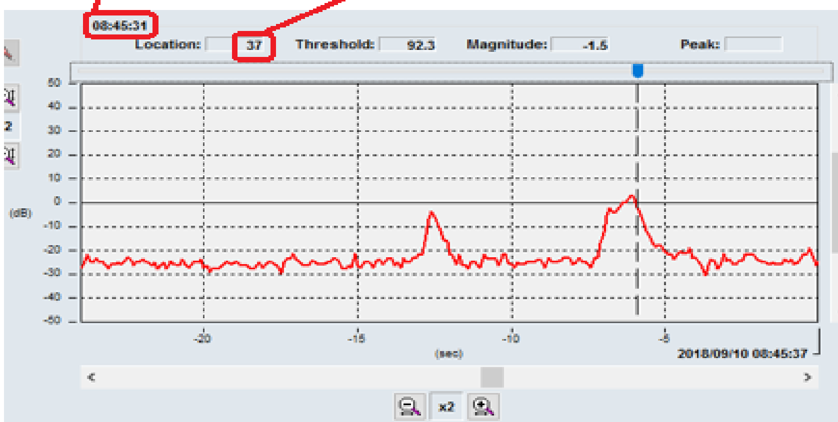


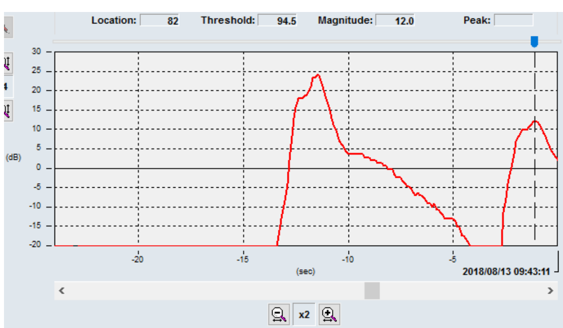
Cable System Evaluation

- Buried cable RADS Data
  - Continuous collection of detections with
    - Location along cable (m)
    - Cable segment (zone)
    - Signal strength
- Recorded video of test area
  - High quality near infrared (NIR) sensitive camera
  - NIR illuminator(s)
  - Continuously recorded video with additional events of interest
- Other recorded data
  - Maintenance activities
  - Road traffic
  - Pedestrian activities

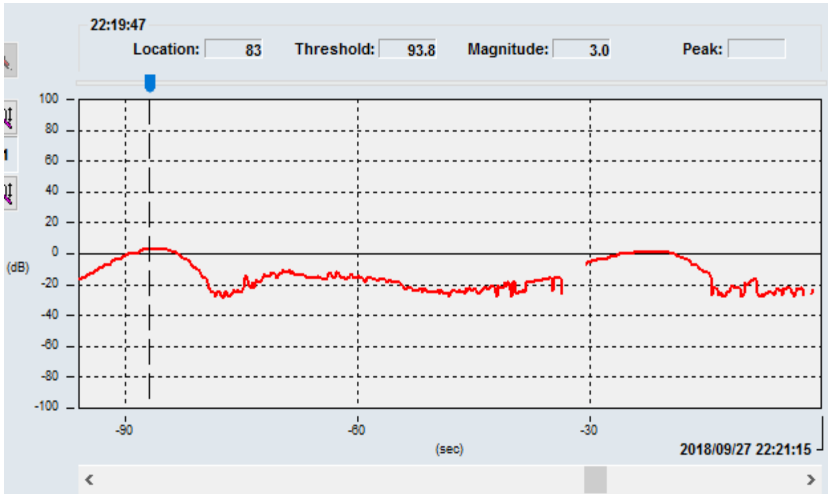
Data Collection (FalseNegatives,FalsePositives)

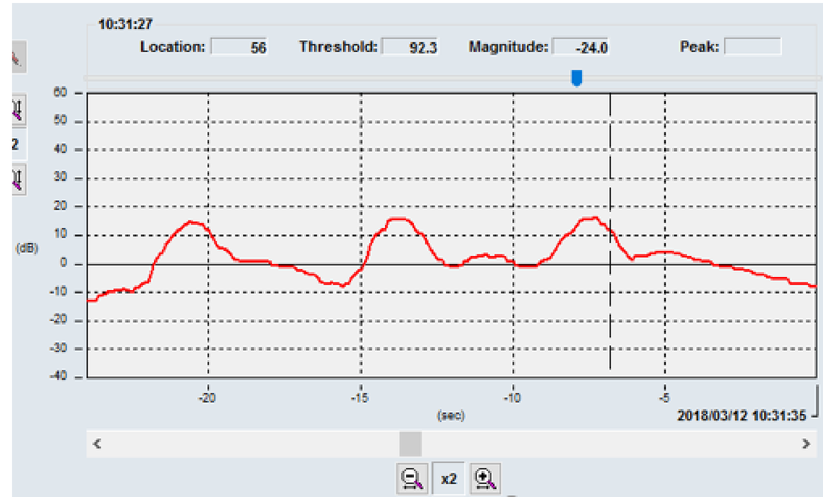
Time	Event
2018/09/09 21:26	Alarm Active: Side A Meter = 86 (Zone 2)
2018/09/10 02:59	Alarm Active: Side A Meter = 85 (Zone 2)
2018/09/10 06:49	Alarm Active: Side A Meter = 90 (Zone 1)
2018/09/10 08:22	Alarm Active: Side A Meter = 86 (Zone 2)
2018/09/10 08:45	Alarm Active: Side A Meter = 97 (Zone 1)
2018/09/10 08:45	Alarm Active: Side A Meter = 37 (Zone 1)
2018/09/10 10:21	Alarm Active: Side A Meter = 90 (Zone 1)
2018/09/10 10:21	Alarm Active: Side A Meter = 82 (Zone 2)
2018/09/10 10:22	Alarm Active: Side A Meter = 83 (Zone 2)
2018/09/10 10:22	Alarm Active: Side A Meter = 86 (Zone 2)
2018/09/10 18:49	Alarm Active: Side A Meter = 93 (Zone 1)





Water Effects





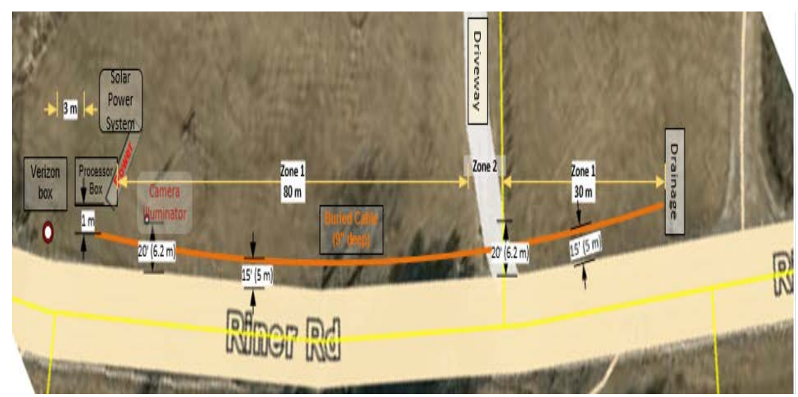
System Reliability

$$R = N_{VD} / N_{RE} = N_{VD} / (N_{VD} + N_{FN} + N_{FP})$$

Month	Total # of Animals		Valid Detections	False Negatives	False Positives	Hours Analyzed	Reliability R (%)
	Deer	Coyote					
Nov	3	0	3	0	0	336	100 @ 13.5 dB
Dec	26	0	136	0	0	660	100 @ 13.5 dB
Jan	8	0	71	0	0	672	100 @ 12 dB
Feb	14	0	26	0	0	744	100 @ 12 dB
Mar	5	0	38	0	0	720	100 @ 12 dB
Apr	10	0	80	0	0	700	100 @ 12 dB
May	14	0	52	0	3	744	95 @ 12 dB
Jun	34	3	90	2	12	720	98 @ 12 dB
Jul	33	0	83	1	0	744	100 @ 12 dB
Aug	8	1	24	0	0	720	100 @ 12 dB
Sep	17	0	50	0	0	720	100 @ 12 dB
Total	**172**	4	**682**	3	0	7480	**99.4**

1st Zone 1 (5m to 80m)	Zone 2 (81m to 86m)	2nd Zone 1 (87m to 120m)
86	12	78

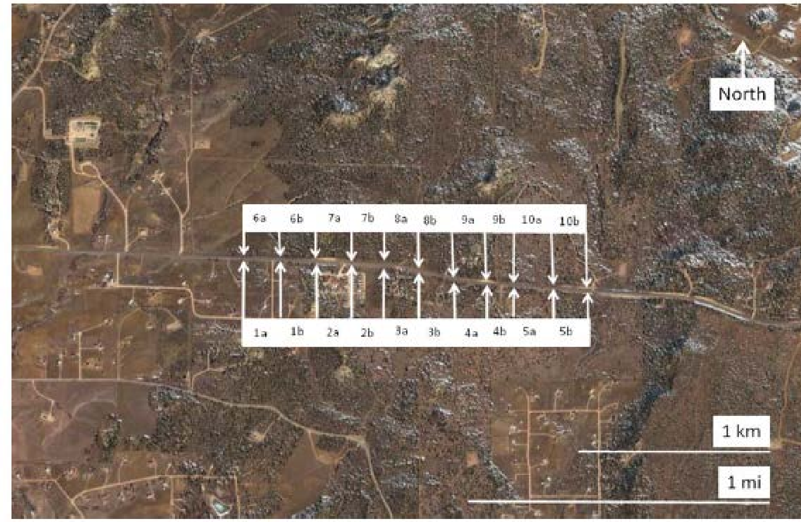
Month	18:00 to 21:00	21:00 to 00:00	00:00 to 06:00	06:00 to 09:00
Nov	2	1	0	0
Dec	3	8	13	2
Jan	0	1	7	0
Feb	1	2	11	0
Mar	0	1	4	0
Apr	1	2	7	1
May	0	3	9	2
Jun	3	2	27	2
Jul	2	3	25	3
Aug	0	2	7	1
Sep	1	1	14	1
Total	13	26	124	12



Other Buried Cable RADS Implementations

- US Highway 160 near Durango, CO
  - Marcel Huijser et al.
  - Testing 2009 - 2011
  - Senstar Permatrax then Omnitrax tested
  - High level of false negatives – 71%

- RADS test facility near Lewiston, MT
  - Marcel Huijser et al.
  - Testing ~2009
  - Domesticated animals as subjects
  - Senstar Permatrax tested
  - Very low levels of false positives
  - 98% valid detections



Source: Huijser et al. 2012

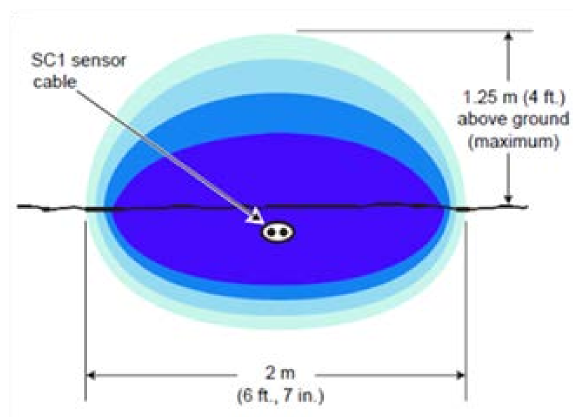

Source: Huijser et al. 2012

Conclusions

- When installed correctly and in a suitable location BCADS can reliably detect large animals (98%)
- BCADS signal response can differentiate between various types of intruder crossings (e.g. animal vs. vehicle)
- Possible interference from traffic
- Detection threshold not affected by moderate snowfall

Potential Pitfalls

- Poor site application
  - Terrain
  - Proximity of nearby metal objects (e.g. guardrails)
  - Distance to road
  - Vehicles and maintenance equipment on driveways or over cable
- Damage from burrowing animals
- Lightning damage
- Overland water flow
- Deep snow
- Soil voids near cable (compaction issue)
- Lack of ingress/egress determination

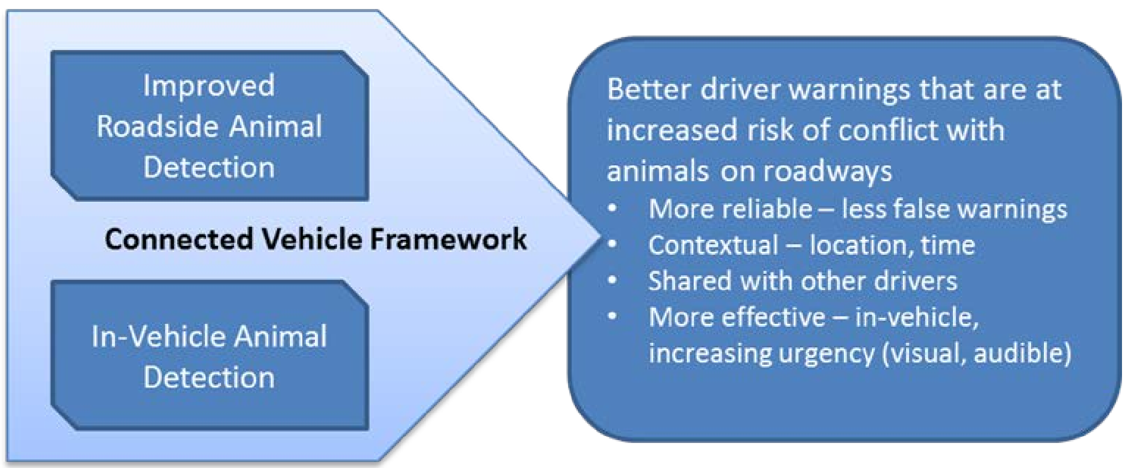


Recommendations for VDOT

- VDOT 'AVC Toolbox'
  - Continue to monitor current site
  - Verify AVC data (police, DMV, carcass removal)
  - New BCADS implementation at high AVC sites
- DVC mitigation at hotspots
  - Hotspot identification
  - Install BCADS
  - Create BCADS guidance manual

Path Forward?

- AVC warnings via VDOT safety app based on carcass count, land usage, environment, temporal condition, etc.
- Pairing fencing with BCADS
- Use of AI to improve
- In-Vehicle warnings via onboard equipment (OBE) or mobile device from BCADS (leveraged with ongoing work)



Presentation End

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Questions?

Today’s Panel

#TRBWebinar

- Moderators: Dan Smith, *University of Central Florida, &* Nova Simpson, *Nevada Department of Transportation*
- Fraser Shilling, *University of California, Davis*
- Hao Xu, *University of Nevada, Reno*
- Andy Alden, *Virginia Tech Transportation Institute*

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