ADS SENSOR DEGRADATION TESTING, MODELING, AND DETECTION

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GCAPS/VTTI

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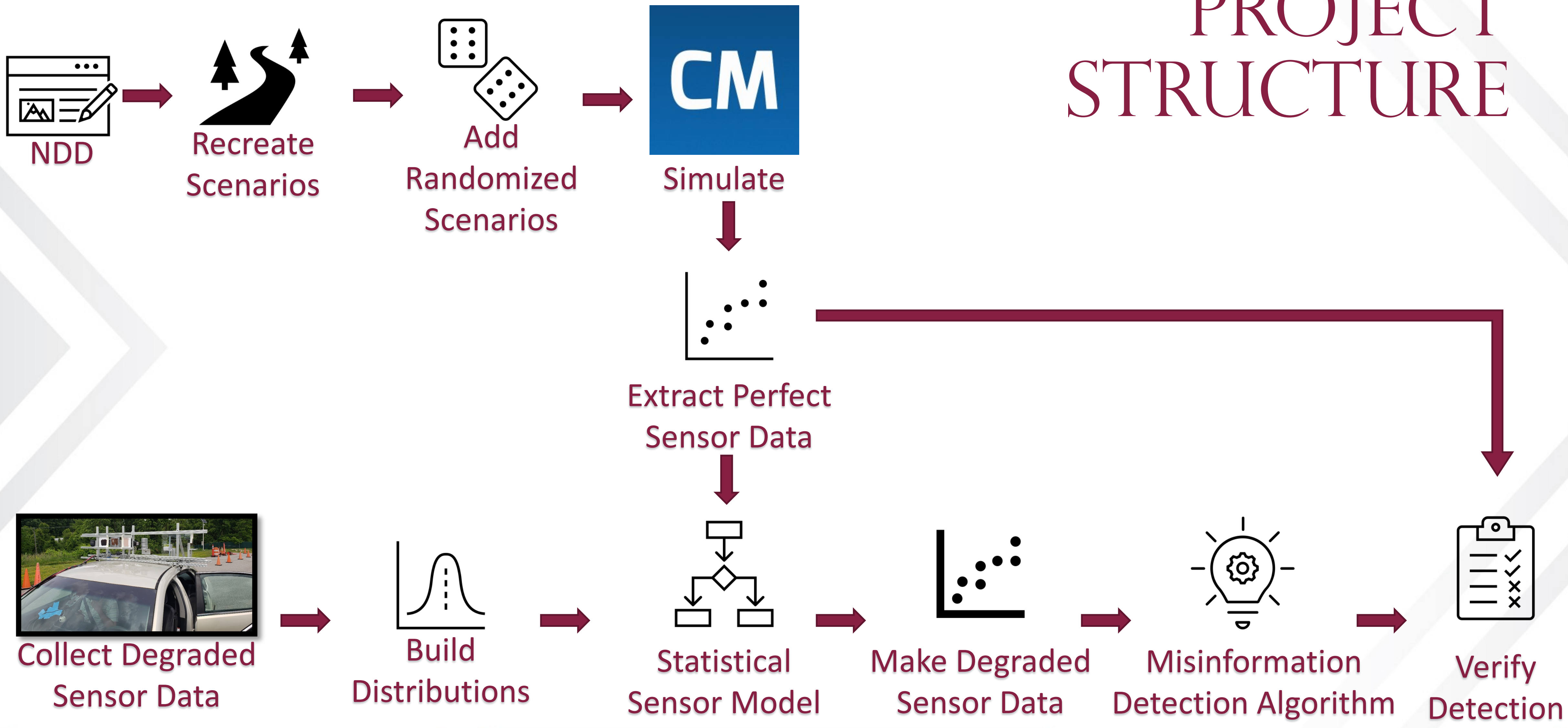
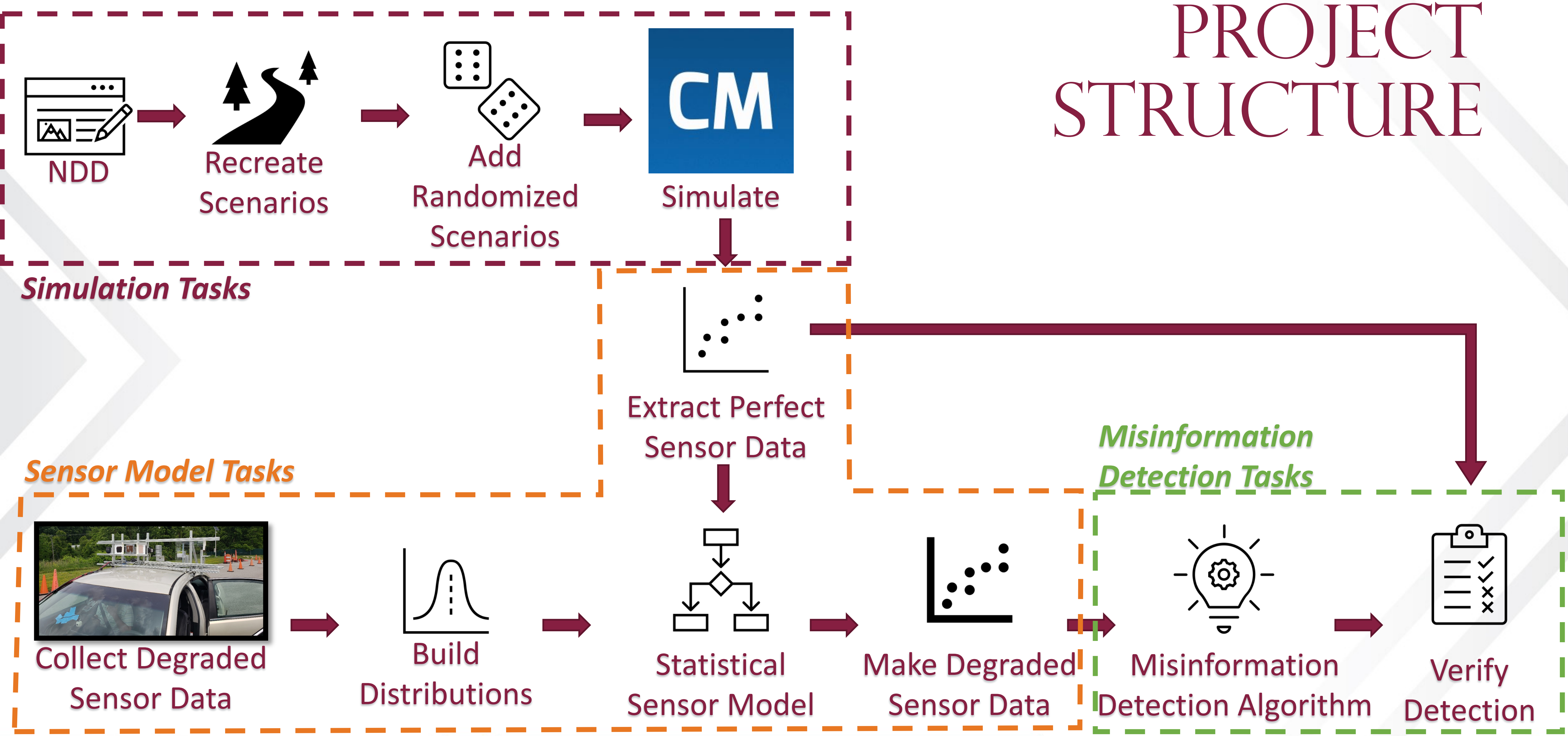
PROJECT SUMMARY

- The project sponsor, Commonwealth Cyber Initiative (CCI)
  - Wanted to explore misinformation that may be sent to the sensors of an Automated Driving Systems (ADS), and our previous work evaluating sensor degradation is a good starting point
  - The project goal was to develop a sensor degradation detection algorithm in simulation
- Virginia Tech Transportation Institute (VTTI)
  - Provided Naturalistic Driving Database (NDD) for us to recreate scenarios for simulation
  - Provided test equipment and facilities to collect sensor data that were used to build sensor models to generate simulation data
- Old Dominion University (ODU)
  - Provided/developed deepPOSE data, to integrate localization data to the algorithm
- Project Outcomes:
  - A virtual framework was developed generate simulation data based on real scenarios and actual sensor responses
  - The process of collecting the sensor data, creating sensor models, and utilizing simulation for an algorithm development toolchain

PROJECT STRUCTURE



PROJECT STRUCTURE



SIMULATION TASKS

NDD SELECTION

- 100 Events selected from NDD
- Rural, highway, urban settings
- Event Parameters:
  - Event Severity
  - Crash Severity
  - Incident Type
  - Weather
  - Road Alignment
  - Lane Occupied
  - Traffic Density
- 500,000+ possible factorial combinations

	Value	Count	Percent
EVENTSEVERITY	Additional Baseline	12581	30.3%
	Balanced-Sample Baseline	19998	48.1%
	Crash	1855	4.5%
	Crash-Relevant	42	0.1%
	Near-Crash	6923	16.7%
	Non-Subject Conflict	140	0.3%
CRASHSEVERITY	I - Most Severe	113	0.3%
	II - Police-reportable Crash	184	0.4%
	III - Minor Crash	777	1.9%
	IV - Low-risk Tire Strike	799	1.9%
	Not a Crash	7087	17.1%
	N/A	32579	78.4%
INCIDENTTYPE	N/A	39182	94.3%
	Pedalcyclist-related	67	0.2%
	Pedestrian-related	169	0.4%
	Road departure (end)	137	0.3%
	Road departure (left or right)	1259	3.0%
	Turn across path	327	0.8%
	Turn into path (same direction)	398	1.0%

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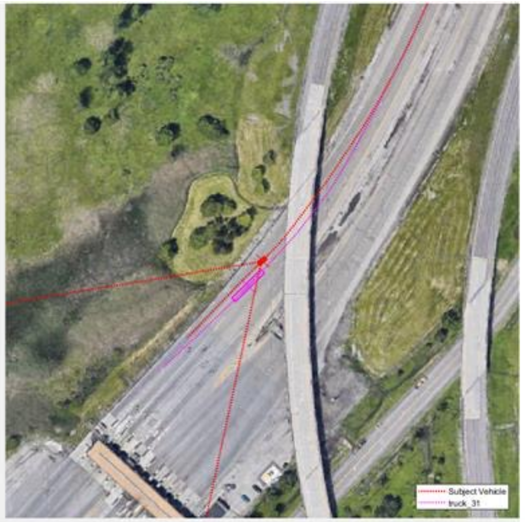
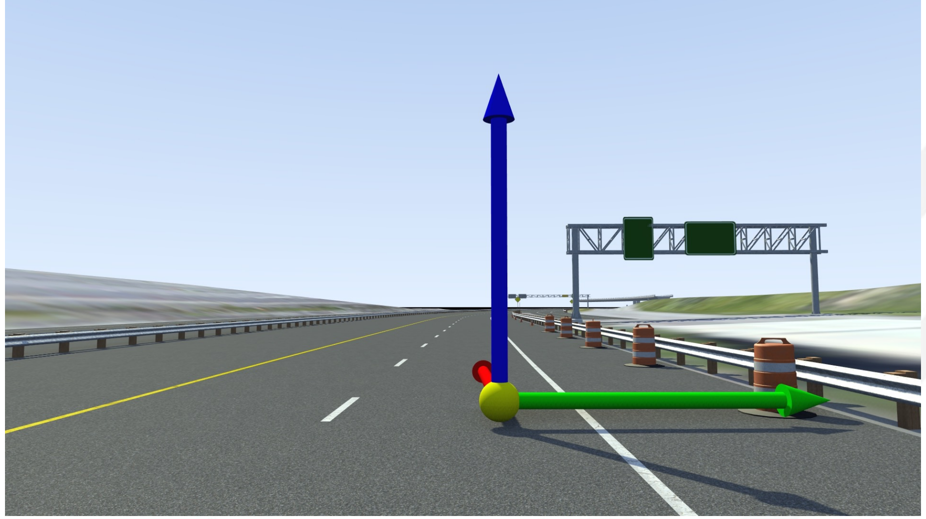
	Value	Count	Percent
WEATHER	Fog	189	0.5%
	Mist/Light Rain	1534	3.7%
	N/A	265	0.6%
	No Adverse Conditions	37516	90.3%
	Rain and Fog	25	0.1%
	Raining	2010	4.8%
ALIGNMENT	Curve left	2796	6.7%
	Curve right	3105	7.5%
	Other	2	0.0%
	Straight	35635	85.8%
	Unknown	1	0.0%
LANE	1	24299	58.5%
	2	9322	22.4%
	3	2576	6.2%
	4	632	1.5%
	5	140	0.3%
	6	12	0.0%
	7	3	0.0%
	Acceleration lane	308	0.7%
	Center 2-way turn lane	123	0.3%
	Deceleration lane	360	0.9%
	Dedicated left turn lane	1188	2.9%
	Dedicated right turn lane	855	2.1%
	N/A	1721	4.1%
DENSITY	A1: Free flow, no lead traffic	14702	35.4%
	A2: Free flow, leading traffic present	11385	27.4%
	B: Flow with some restrictions	11539	27.8%
	C: Stable flow, maneuverability and speed are more restricted	2577	6.2%
	D Unstable flow - temporary restrictions substantially slow driver	872	2.1%
	N/A	464	1.1%

SCENARIO RECREATION

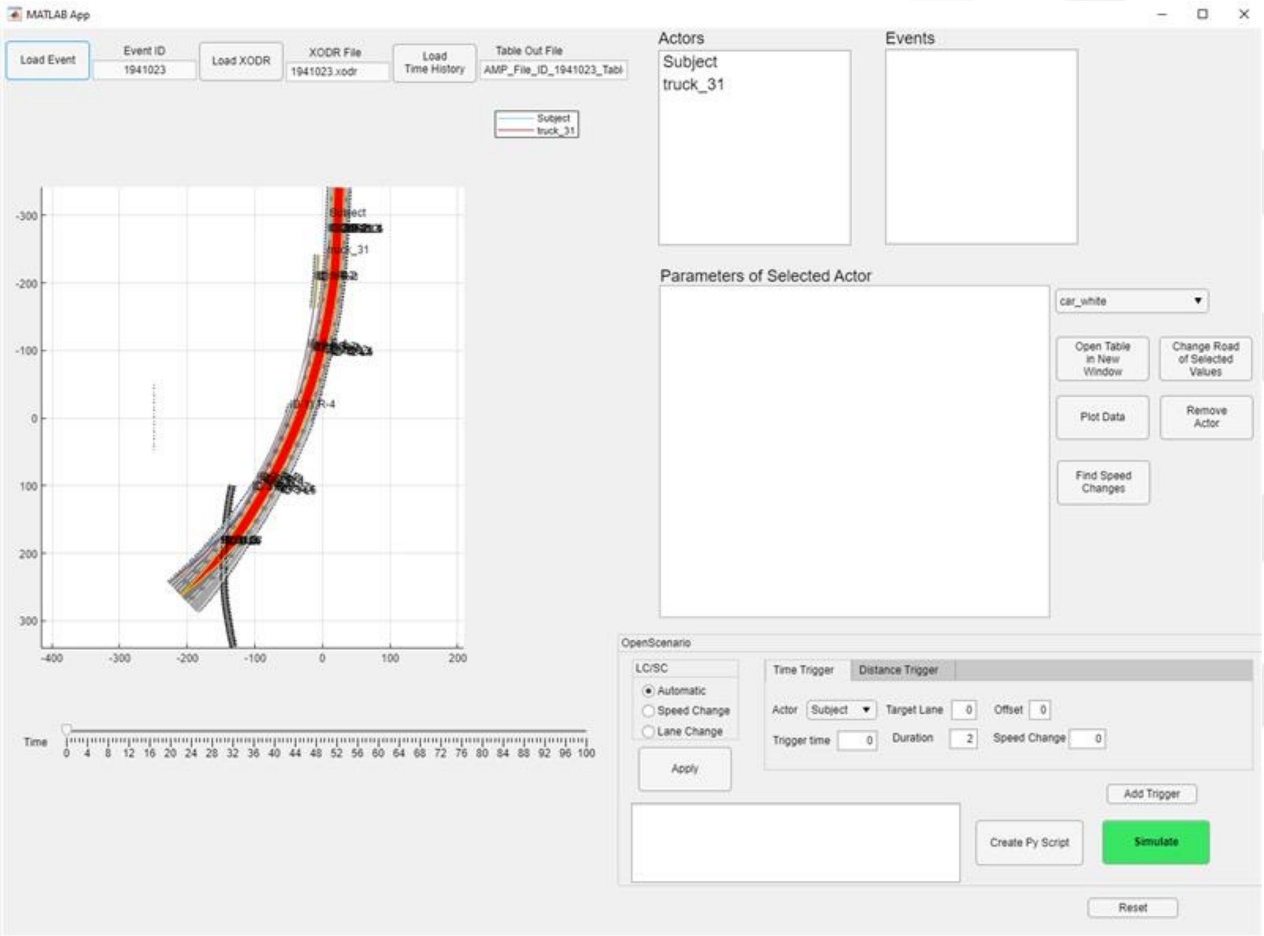
- The environment of the event is recreated in RoadRunner using a combination of frontal video and satellite imagery
- The scene is exported as an OpenDrive file to be used in IPG CarMaker simulation software. The OpenDrive file acts as the drivable road surface for the subject vehicle





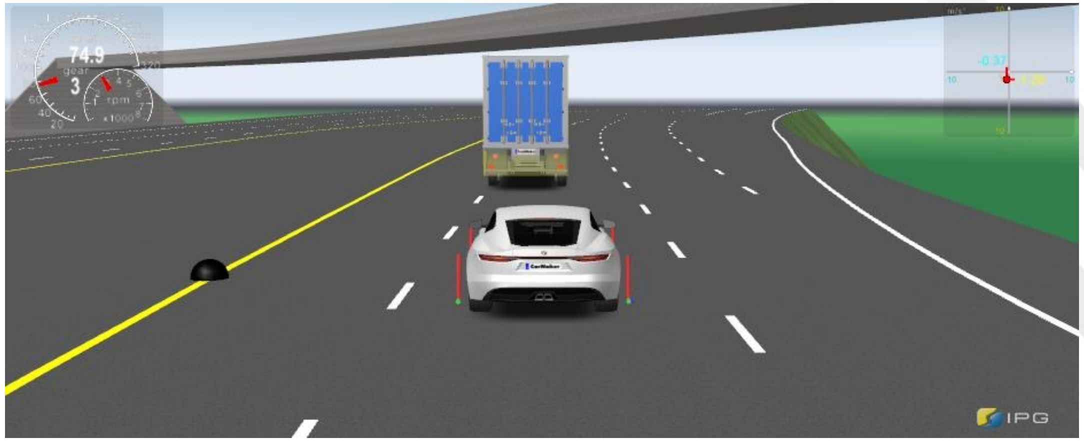
RANDOMIZED SCENARIO GENERATION

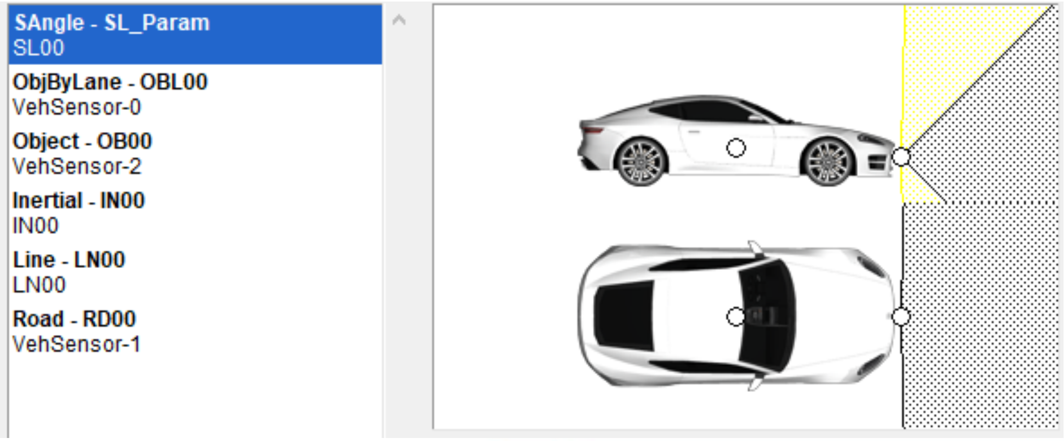
- 100 Events (*Base Events*) expanded to 1000+ by modifying each Base Event's OpenSCENARIO File with at least 9 selected variations
- Variations produced by parameterizing each event and creating events across a parameter range
  - Lane change start and duration
  - Subject vehicle velocity profile
  - Actor position and velocity

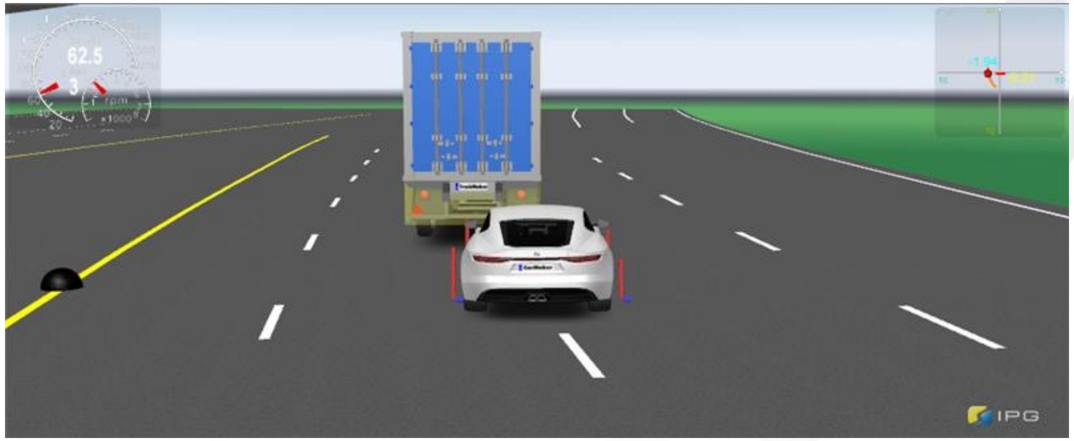


CARMAKER SIMULATION

- Utilize CM sensors to output object-level info
- Select data channels to output from CarMaker
- Run simulations in mass and save time history and sensor data as ERG files
- Process output ERG files in MATLAB for use in sensor degradation algorithm





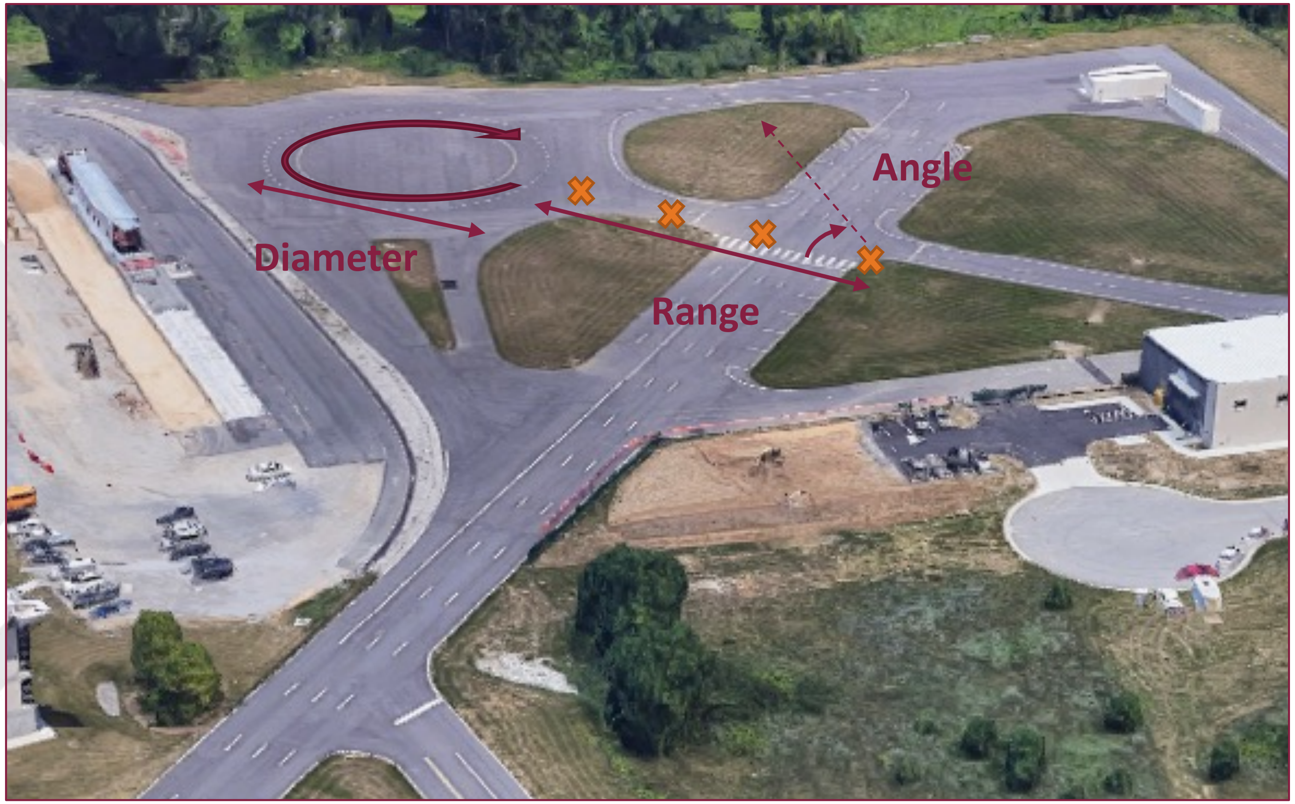


SENSOR MODELING TASKS

SENSOR TESTING SETUP

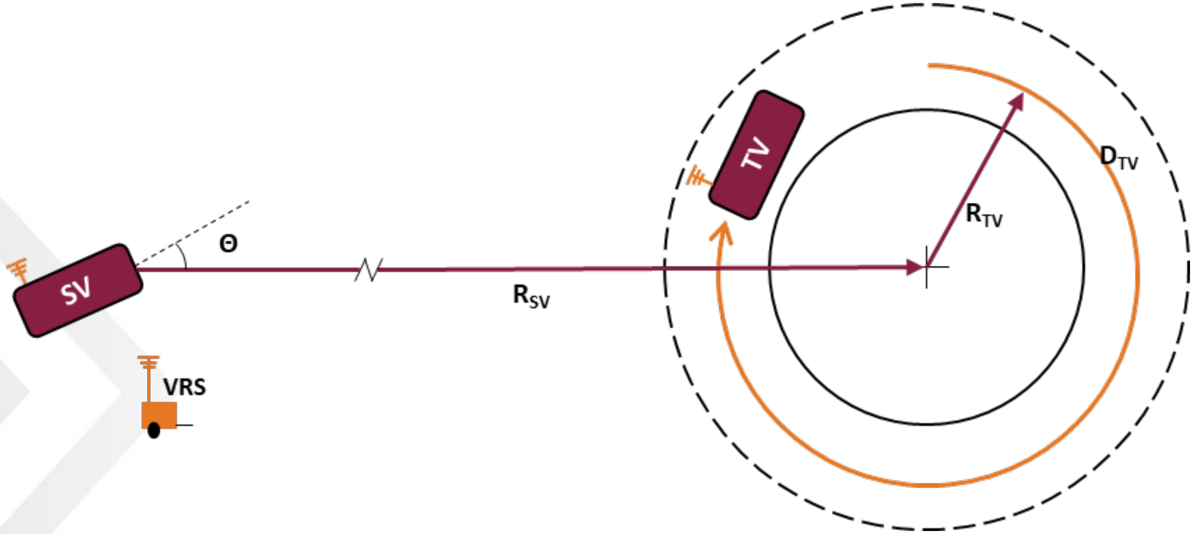
- Functional Tests were used on the VTTI Smart Roads
  - Matches the operational environment while maintaining constraints on unwanted variables
- Two test vehicles were used, a subject and target vehicle
- Sensors and DGPS were integrated into a data acquisition system

FUNCTIONAL TESTS (CIRCLE TRACK)



- Target Vehicle Traveling in circle of various diameters
- Subject vehicle viewing from stationary or moving position
- Measure of accuracy of object detection
- Get viewing angle response
- Measure at multiple distances to linearize

FUNCTIONAL TESTS (CIRCLE TRACK)



SV = Subject Vehicle

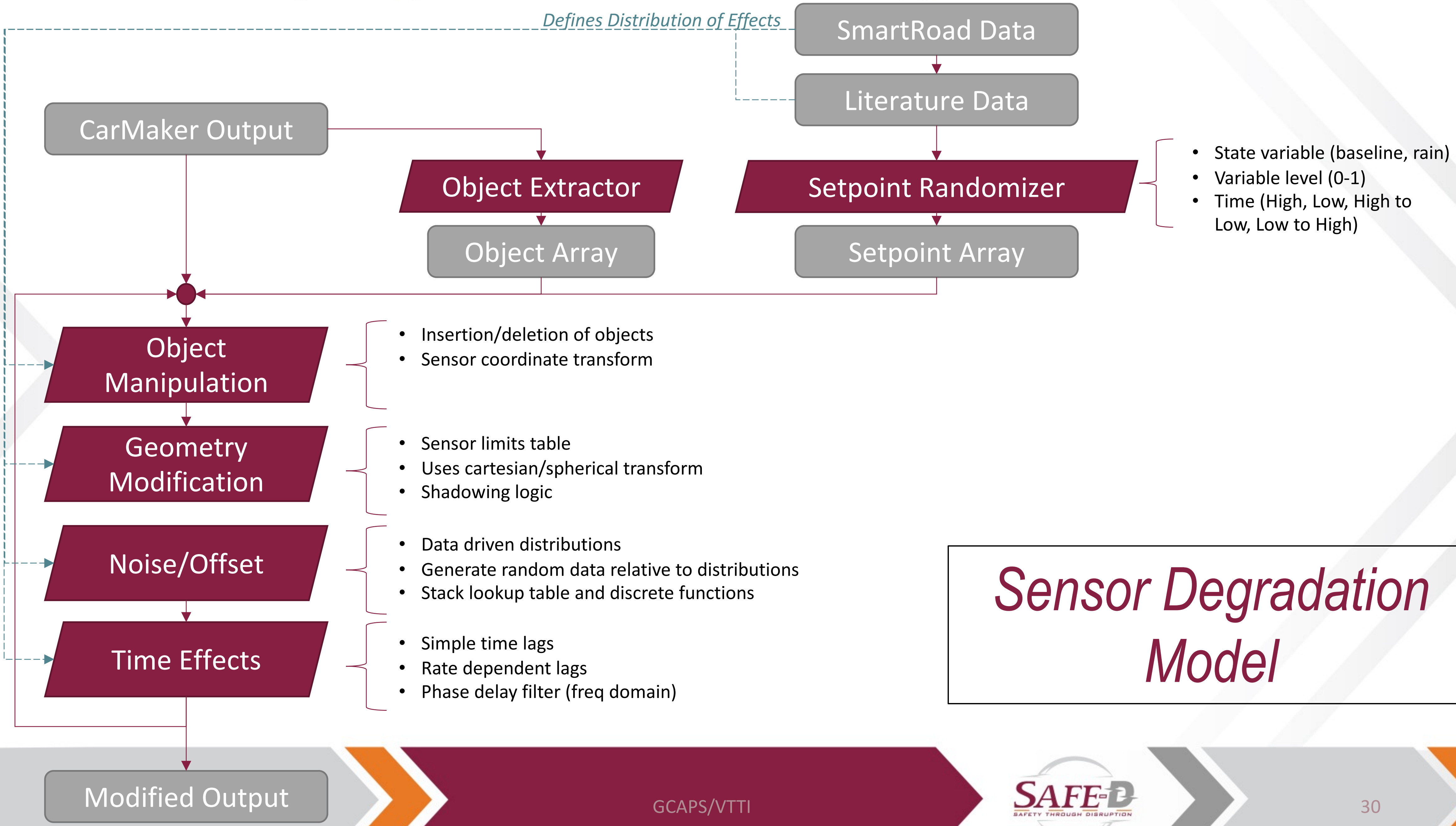
TV = Target Vehicle

Baseline in **Bold*

Variable	Iterations (Surface Street)
Turning Radius (Rtv)	30, **40**, 50 m
Viewing Range (Rsv)	15, 25, **35**, 45 m
Viewing Angle (Θ)	-30, **0**, 30 deg
Target Vehicle Velocity (Vtv)	5, 10, **15** mph

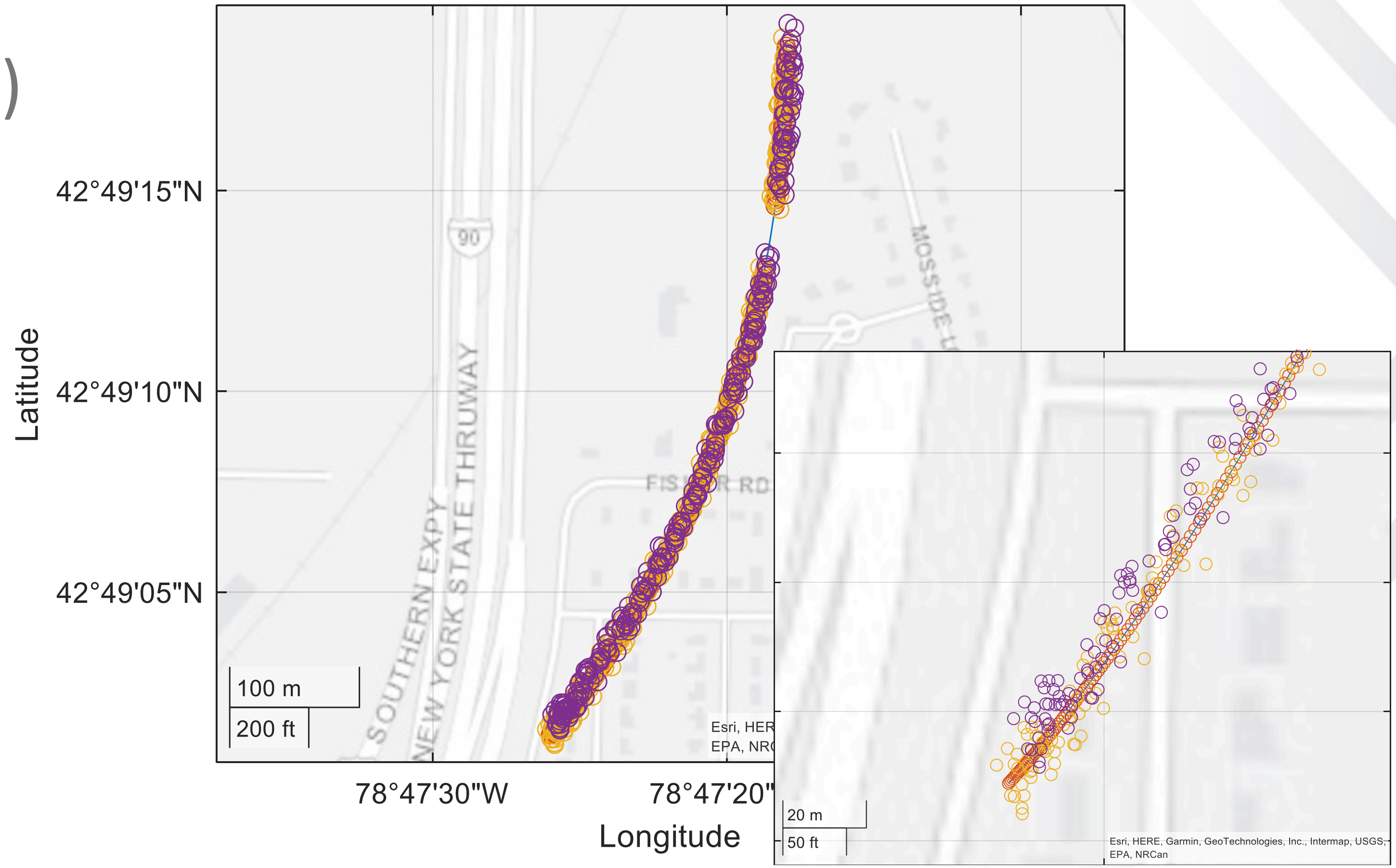
RAIN (DEGRADATION) TESTING

Sensor Degradation Model



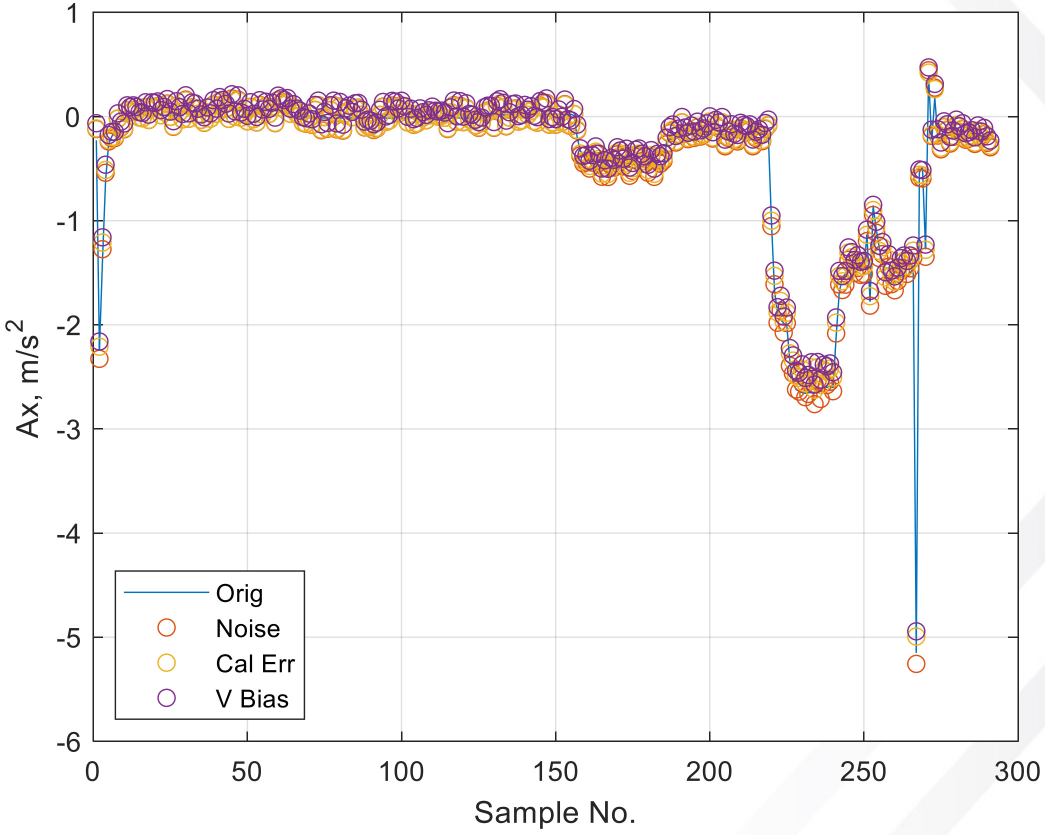
MANIPULATING GPS DATA

- Noise (exaggerated for plots)
- Offsets in lat and long
  - Heading recalculated, then persistence filtered
- Cutouts
- Point Shifts



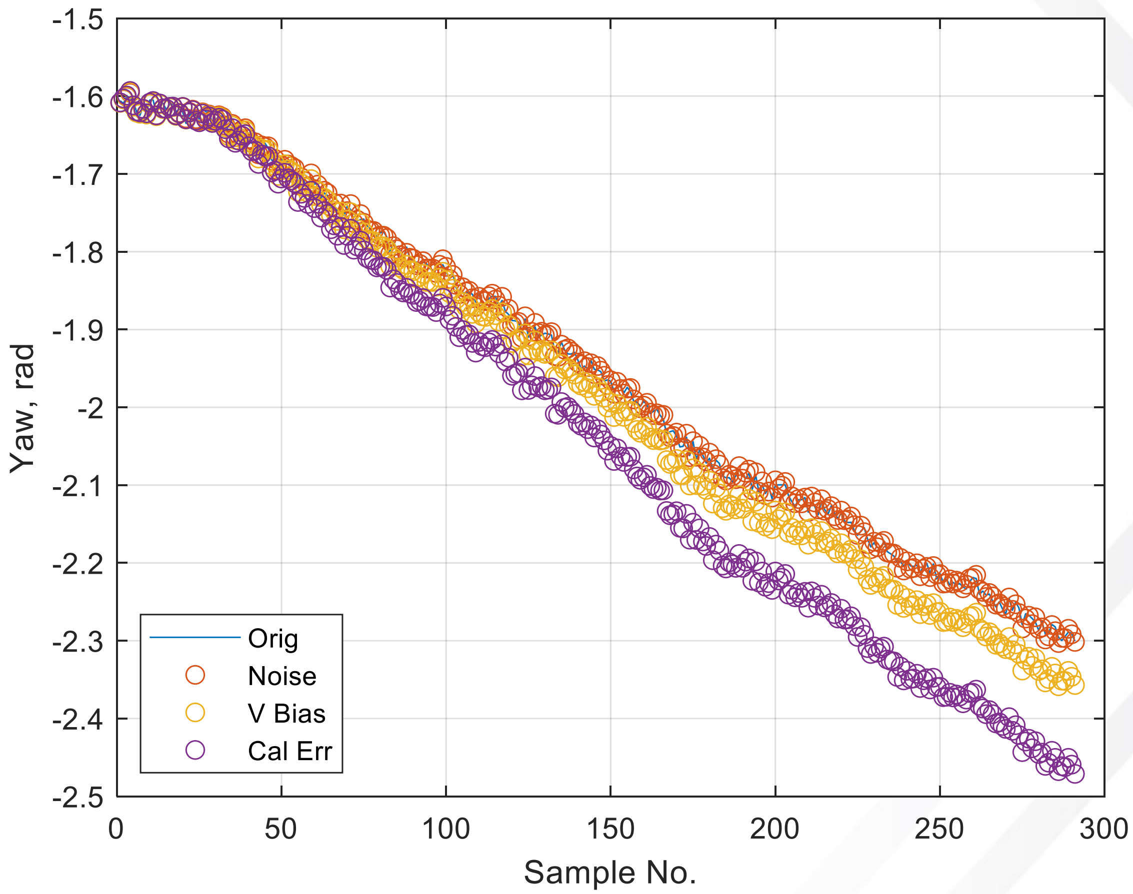
MANIPULATING ACCEL DATA

- Noise
- Offsets from bias voltage
- Calibration error
- Not Included:
    - FRF response ignored because sample rate so low and most accels are flat response in this region
    - Shock decay response (capacitive drain) not included

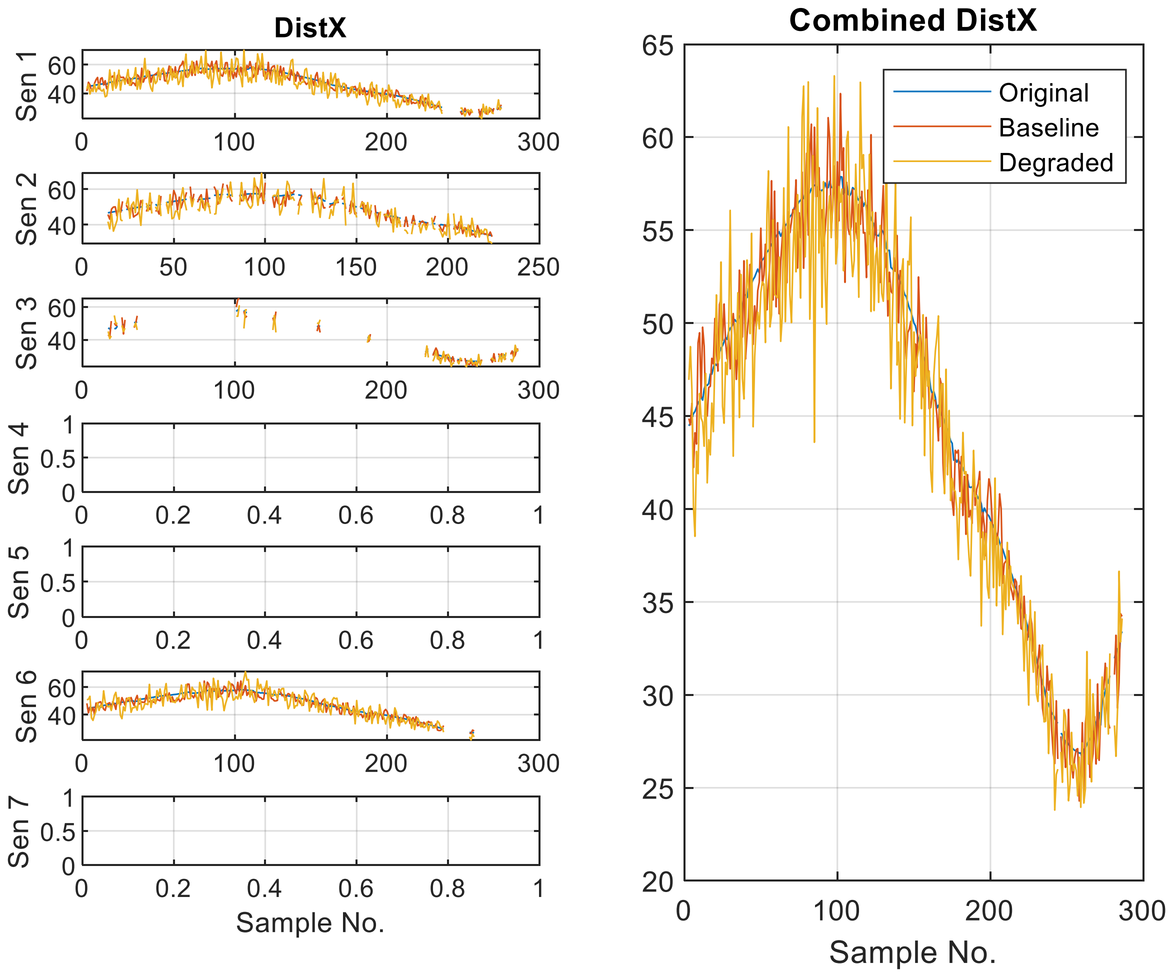


MANIPULATING GYRO DATA

- Noise
- Offsets from bias voltage (accumulated)
- Calibration error
  - Sensitive to derivatives as method of action is torque sensitivity
  - Integrated back to signal



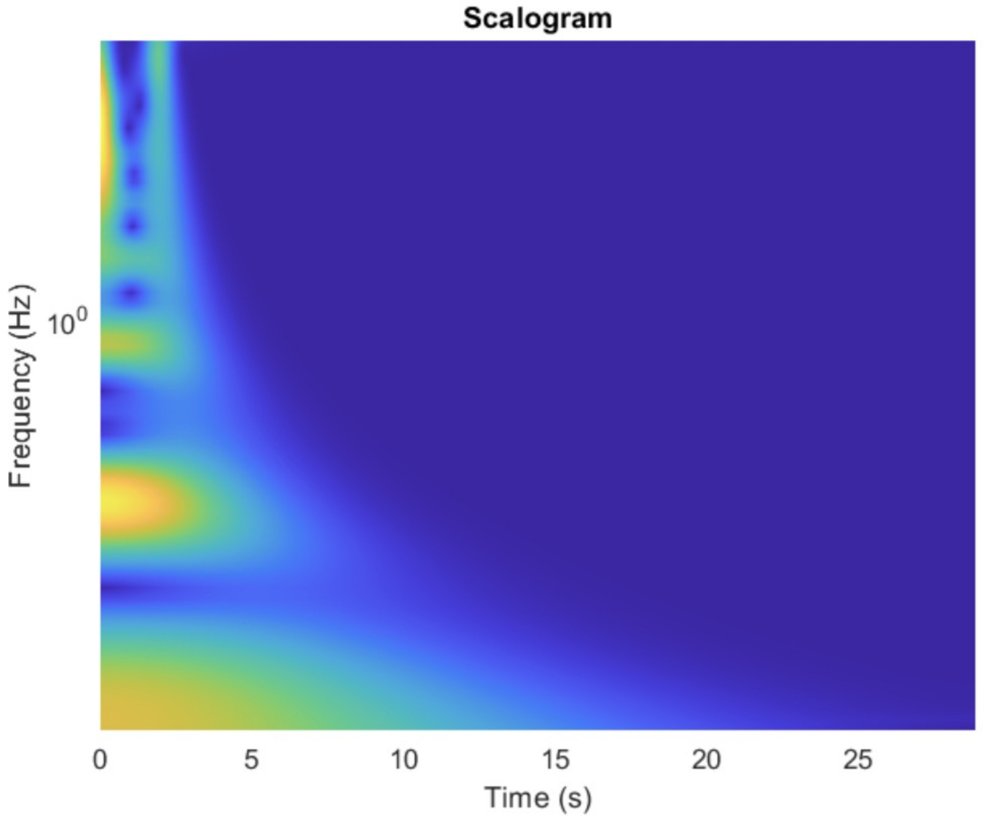
DEGRADED DATA ADDED TO SAMPLE DATA



MISINFORMATION DETECTION TASKS

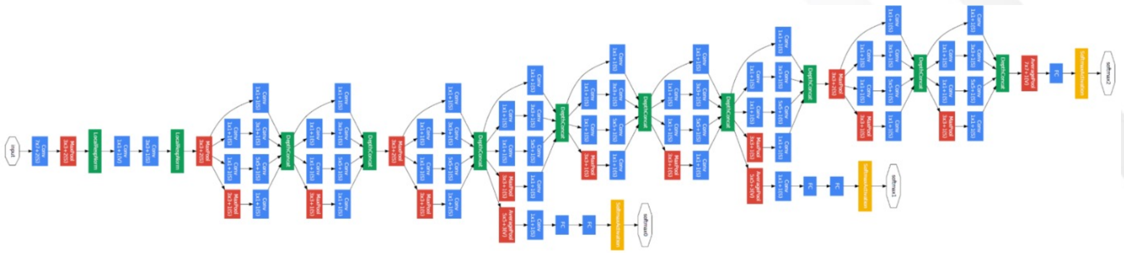
MISINFORMATION DETECTION ALGORITHM

- The trajectory trend gets removed from the fused data
  - Extracts the characteristic response without the unique maneuver information that dominates the signal
- The characteristic response is then converted to a scalogram using the coefficients from a continuous wavelet transform (CWT)

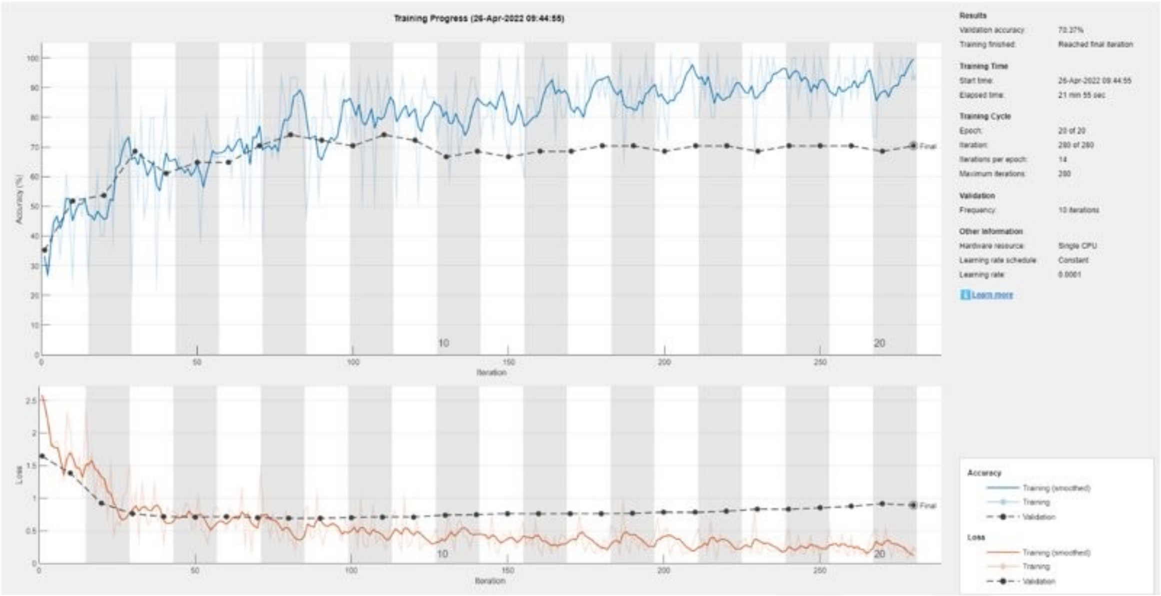


MISINFORMATION DETECTION ALGORITHM

- The scalograms from the CWT are stored as images with a classification label to mark state variable levels
- A GoogLeNet convolutional neural network is trained on the scalogram images to classify state variables to the CWT responses



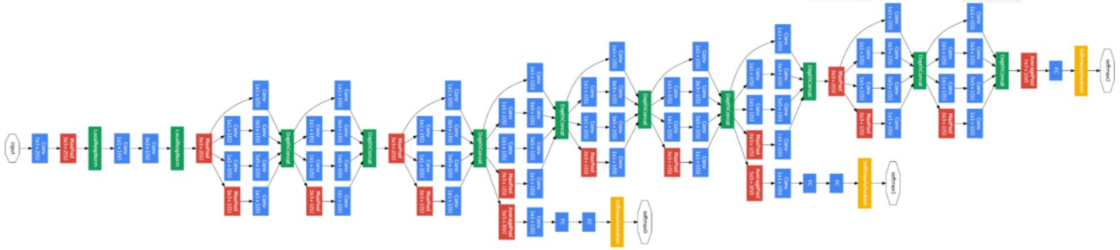
GoogLeNet Architecture



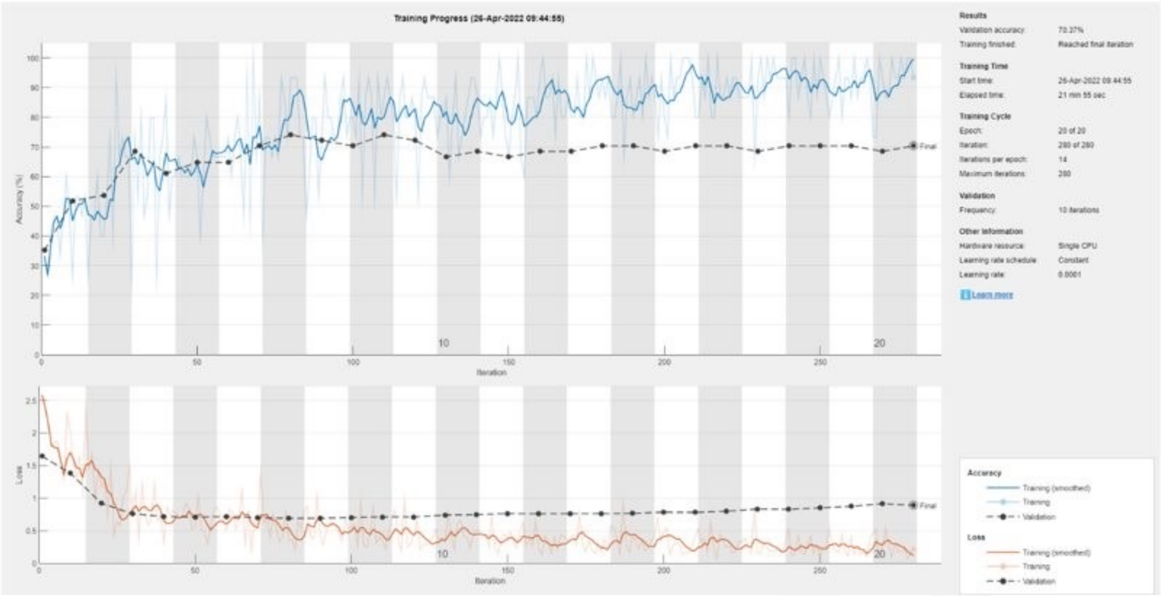
Training the network

MISINFORMATION DETECTION ALGORITHM

- The classification accuracy on the validation dataset was 70.4%
- The data was made to be challenging to the algorithm
  - The classifier was binary, but the degradation was continuous, so light rain was often classified as no rain
  - The event selection was selected to be more challenging safety critical events



GoogLeNet Architecture



Training the network

FUTURE WORK

- Generation of additional simulation scenarios would help increase the training data for the algorithm, though this is a time and effort intensive process
- Collection of additional degradation and emulated misinformation data could expand the classifying capability of the algorithm
- Improvements can be made to the signal preprocessing; perhaps a deterministic layer before the neural network to handle the first order effects

QUESTIONS?