US DOT Intersection Safety Challenge Submission

by Crystal Clear Automation, LLC

Optimizing ISS Generator (OIG)

"Everything except the Kitchen Sink" Intersection Safety Optimizer Platform

Concept Overview

Smart intersection sensors have the potential to save lives and prevent serious injuries.

The effective deployment of these Intersection Safety Systems(ISS)es, at scale, has several obstacles.

Using current traffic engineering practices is too labor and time intensive to deploy these systems optimally at scale. The human brain is not up to the task of solving the many multi-dimensional problems in the evaluation, design and utilization of smart sensor systems.

Our concept ISS submission is not a single ISS, rather it is an AI driven platform that generates individual ISS systems optimized for each intersection.

The proposed system consists of these modules and data flow between the modules..
Planning – Designing – Deployment – Operations – Monitoring - Maintenance

Each of these modules performs its primary functions with Genetic Algorithms and a variety of AI models and methods.

To produce an intersection safety system (ISS) with a highly reliable performance in road user trajectory and crash prediction plus real-time mitigation, it is essential to design each individual ISS with the:

- right selection of sensor types and quantity.
- optimal placement of those sensors to maximize intersection coverage
- real-time generation of optimal sensor data fusion weights

The proposed platform will utilize a data model driven approach, that will support all vendor and open source technologies. Allowing traffic engineers to apply all available technologies to improve safety and equity.

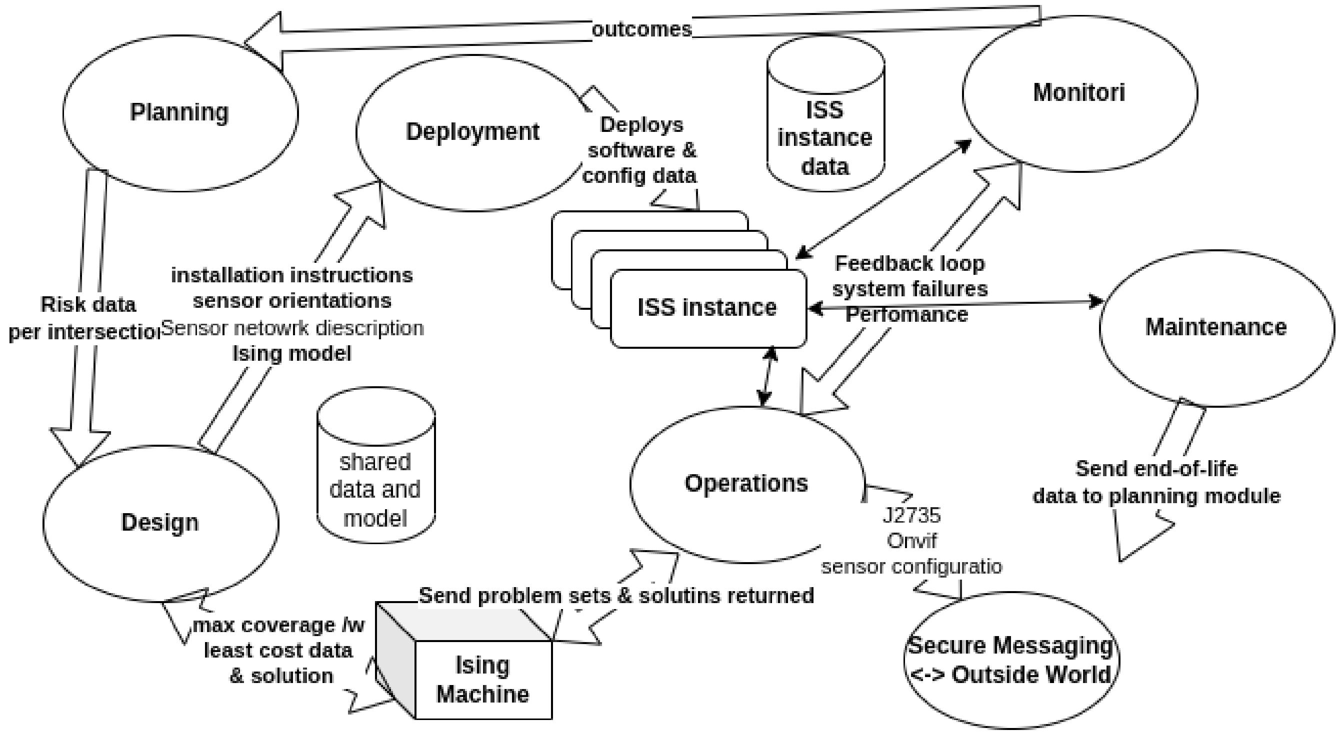
The proposed ISS generator will produce an ISS for the defined US DOT challenge test site sensor network.

The proposed system an AR/VR simulator that will both produce video streams video streams of high resolution simulated traffic and digital twins of other intersections.

This allows closed site AI training of many remote intersections, producing more reliable results.

We have successfully used synthetically produced image datasets for weed detection, classification and segmentation. We found greener fields work better on the trained model we started with. Retraining with brown grass seed images

I see far by standing on the shoulders of giants.



Fi 1. Planning, design and deployment modules run on central traffic control center. Operations, monitor, maintenance and secure messaging modules run at intersections and collectively an ISS instance.

Planning Module

State and local DOTs typically have a specific amount of funding available for risk mitigation of all their intersections and roadways.

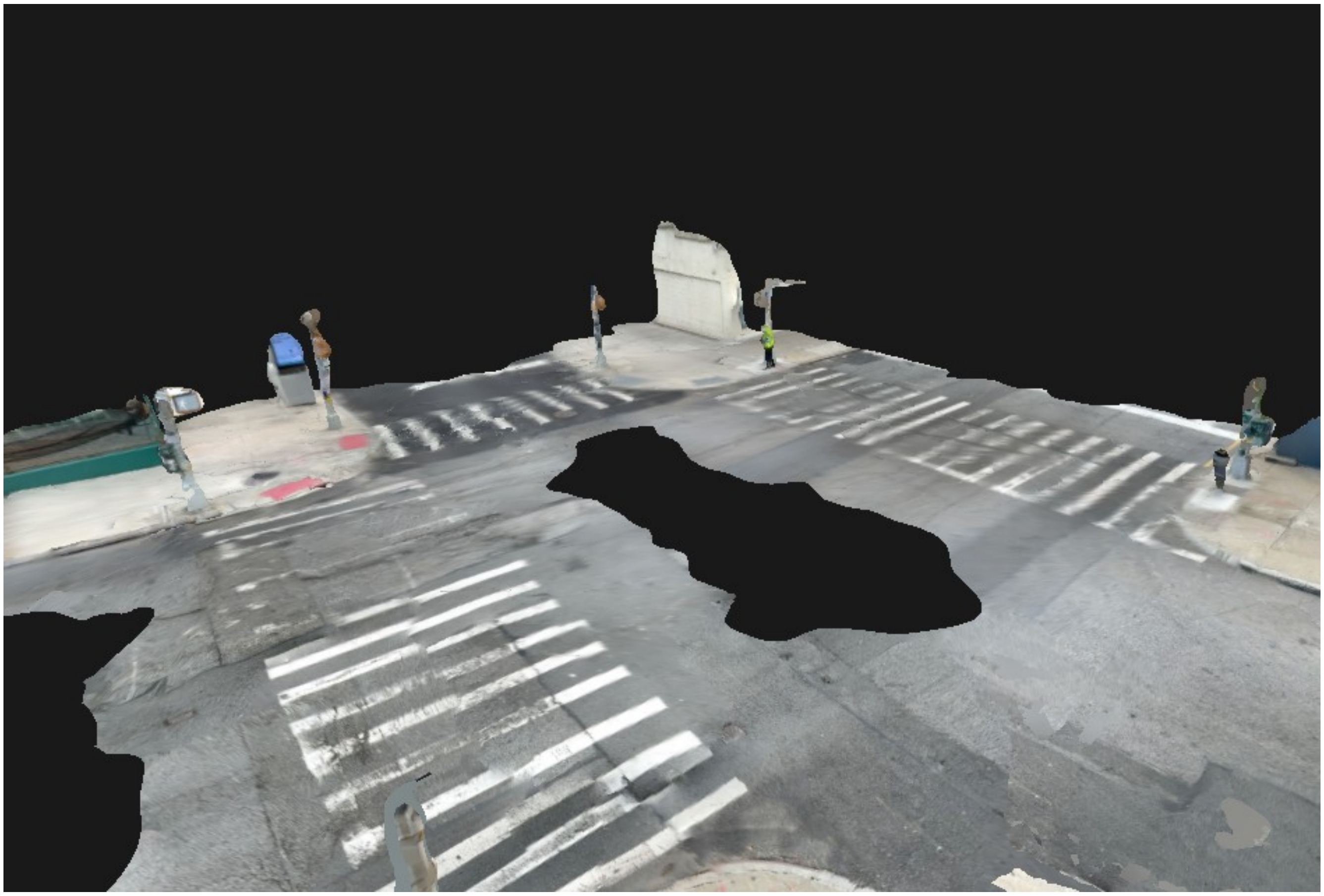
We propose a planning module optimized to provide DOTs the biggest bang for their Intersection Safety buck.

We start by creating a realistic simulation of all intersections and roadways. There are sme 210,000+ signalized intersections in the US. If we optimize the simulation first, then we can optimize the real world after the simulator makes all the mistakes.

Crowd Sourcing

3D Digital twins of each are captured using crowd sourcing via a gamified mobile app and mounting low cost cameras on buses and other government vehicles.

Here is a NYC intersection scanned with and iPhone in 15 minutes. Over time the quality of the 3D mesh improves.



The app will be a Massively Multiplayer Online Roll Playing Game(MMORPG).

Things to be crowd sourced:

- digital twin intersections and roadways
- Road inventory at intersection and roadways
- what is wrong with the intersections annotations (ie. croswalk crossing time to fast, blind curve.)
- identifying site specific local characteristics impacting social equity on crash safety
- defining and implementing social equity and safety solutions
- provide distributed processing for training users on local intersection models.

Risk Analysis

We will be mapping the collision risk by sensor-RU location, direction is look toward and the 3D envelope of its effective volume in the intersection, these results datasets will be driven by a ever growing number of intersection and road user characterizations.

Our ISS optimizer generator will be using a targeted ground state for not just safety but for social equity. We are setting the ground state for safety at 0 crashes.

The ground state for social equity to be an equal crash risk across all neighborhoods within a jurisdiction. ISS generator later modules will use actual crash and near miss data to feedback correction data to the planning models and human curators to correct the social equity disparity model and/or look for additional factors that are impacting social equity.

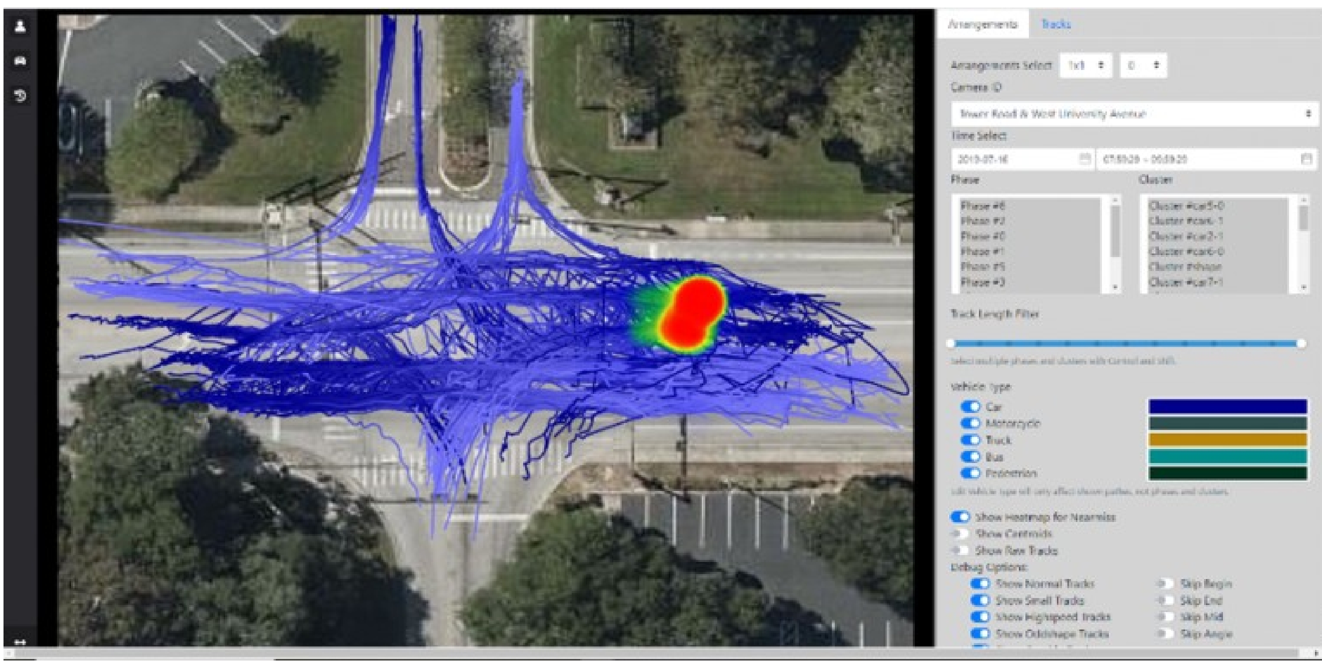
The commercially deployed will also optimize intersections for

By performing a road network risk analysis, DOTS can prioritize intersections that will receive those funds. Current industry practice for road network risk analysis is done using historical crash data and more recently using similarity of static road conditions like:

- rural vs urban road
- speed limit
- sidewalks
- number of lanes
- lines of sites for each road user
- automated generated of permanent and predicted occlusion and other interference in road user perception
- etc

We propose a system that adds the uses of historical road user behavior(tracking, actual speeds, braking distances, near misses, etc) and dynamic road conditions like weather, level of congestion, lighting, etc.

Team member Sanjay Ranka has already performed some of this work in Gainsville, Florida.



Heat map of near misses in intersection locates high risk intersection and specific problem areas.

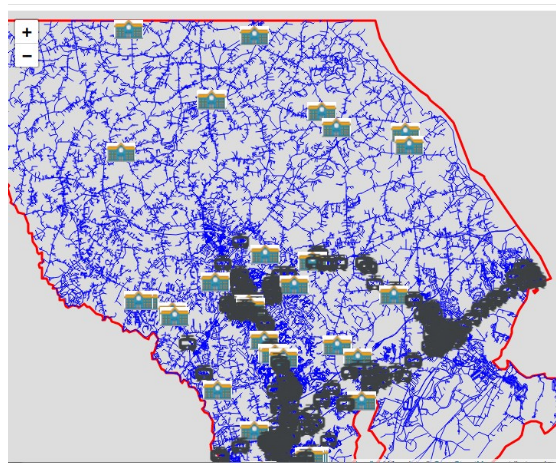
The planning model uses a 3D digital twin mesh that is registered to the GPS coordinate system.

This allows the site specific characterization of each intersection. This allows the automation of deep learning about the relationship of spatial data not just for a static intersection but real-time impacts of spatial temporal data. For instance researchers know line-of-sight and stopping sight distance (**SSD**) contribute to crashes, but have trouble assigning relationship metrics to crashes because their effects on crash risk are very case specific.

AI deep learning generates risk data sets. For example, a driver or vulnerable road user(VRU) has fast response to crash danger with the sun at their back and get blinded looking into the sun. Sun glare is correlated to ~9000 accidents a year.

We have already applied road user detection on public traffic cam video streams. Generates object information overlaid on original stream. We have also take a remote traffic camera stream and feed it into an commercial AI analytics and got similar performance as real traffic scenes.

Simple vehicle detection overlay system for ~800 Maryland DOT traffic cameras. Provides Vehicle counts and road characteristics with no deployment costs.



our software extracts roadway and points of Interest from open street maps by jurisdiction. Here is a pull of Hardford County Md's road center lines, schools and bus stops

Smart Intersection Systems Characterization

We will provide a system to test performance of each vendor solution in 3D space and provide a performance data cloud of each systems predictability of detecting, classifying and segmenting a wide variety of expected road objects. Multiple data clouds will be produced for each sensor, provide result under a variety of expected road conditions:

- Weather
- Lighting
- Time of day
- congestion
- Vehicle speeds
- Pedestrian traffic loads
- etc

The test platform will require performance metric in not only detecting and identify road objects, but also it performance in providing road object:

- Speed
- Trajectory
- Mass – kinetic energy
- Variance – ie. erratic/reckless driving or drunk driving

These metrics will be come very useful as autonomous and driver assisted system fill the roads. The ability of these systems to make real-time decisions to minimize death, serious injuries and property damage, would be enhanced by have real0time access to this type data. They like humans will be presented with a choice of the "lesser of two evils". We believe with the emergence of super intelligent AI vehicle and road side sensing system will be able to use gradient descent and other methods to make such real-time choices. That why we have included the development of a roadside/intersection coherent quantum Ising machine to provide the processing power for this real-time decision making capibilities.

Social Equity Analysis

In order to optimize **ISS** generation for social equity, we will automatically capture spatial-temporal social-economic metrics.

This would include but not limited to:

- Demographics variance of
  - ratio pedestrian & VRUs to cars
  - street lighting
  - presents sidewalks
  - road conditions
  - truck traffic
  - congestion
  - speed limits
  - actual speed/enforcement
  - Road inventory – existing risk mitigation elements
  - vehicle weight - ratio small cars vs Trucks and SUVs
- Proximity to drinking establishments – Alcohol is the number one contribute to fatal crashes.
- Proximity to parks and schools – income can effect walking vs driving
- Prevalence of nearby major arterial roads

Team member Nathan McNeil we be designing additional risk-social equity relationship models and data analysis algorithms and workflows to uncover causation and fixes.

Crowd Sourcing and automation for Digital Twin capture

In order to deploy at scale, we propose a set of smart phone apps to engage the public to:

- analyze and optimize driver and VRU warning message response
- identifying their local worst intersections and the problem elements of the intersections
- capture the intersection in 3D
- capture intersection road inventory
- gather daily tracking data for a large number of intersections using existing traffic cameras and smart phones
- distribute the Ai learning to smart phones
- receive and spread Vision Zero education
- generate safe routes to School, Parks, etc.

We will release a driver and VRU response game for smart phones. While real-time warning is a nice feature to have, the must have is both visual and audio warning systems that are effective.

Eye tracking software is now available on smart phones. We will add phone motion and on screen buttons to steer or brake response to audio visual warning. In addition to collecting response time and cognition data, the game will use generative AI to evolve better warning systems. Individualized systems would let road users

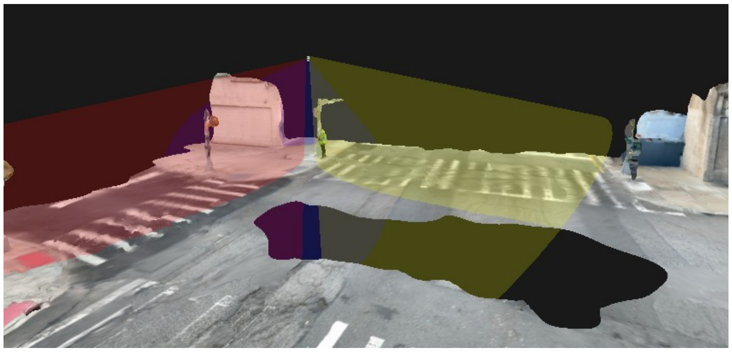
Risk point cloud datasets are sent to the Design Module.

Design

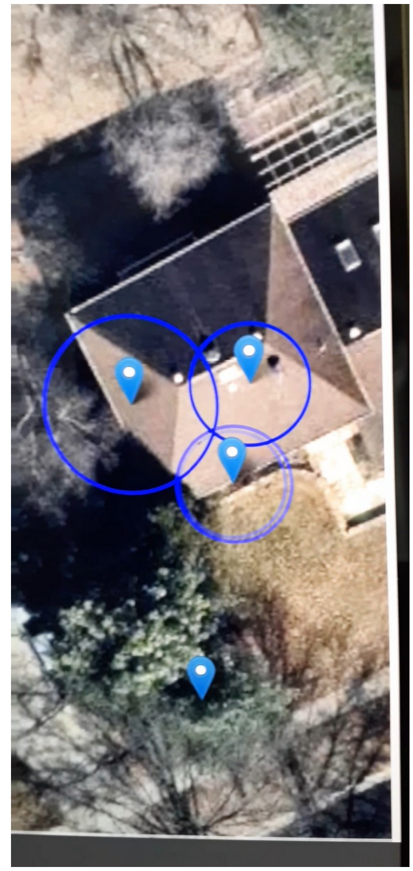
Traffic Engineers Control Panel

This control panel will display the total budget the jurisdiction available for smart intersections/roadways. The traffic engineer and/or elected officials and/or the public will select weights to instruct the AI/GA optimizer to apply in generating the allocation of those funds across all intersection of roadways in that juristion based on the weight(priorities) assigned.

This module will be develop in stages. The first stage will use genetic algorithms to optimize 2D coverage of all sensors. Similar to Velasco et. al. approach[1]. A fisheye lens has a cone a field of view. rectangular lens camera have a pyramid shaped field of view.



Predominate effective field of views of two UWB sensors on in a smart street light controller



Smart camera field of view
iPhone intersection tracking app

iPhone tracking app using UWB nearby interaction
iPhone location were distance streams from 3 or more anchors intersect

Use of graphical user interface(GUI) defines the attributes, attribute weights and formula(s) to define the distribution of funding over all intersections. Later versions of the design module will use AI to define the funding distribution formula.

These later stages will implement a:

- Generative Adversarial Networks(GANS) approach and a nested GA approach
- A nested genetic algorithm approach using a physical annealing accelerator(Coherent Ising machine)

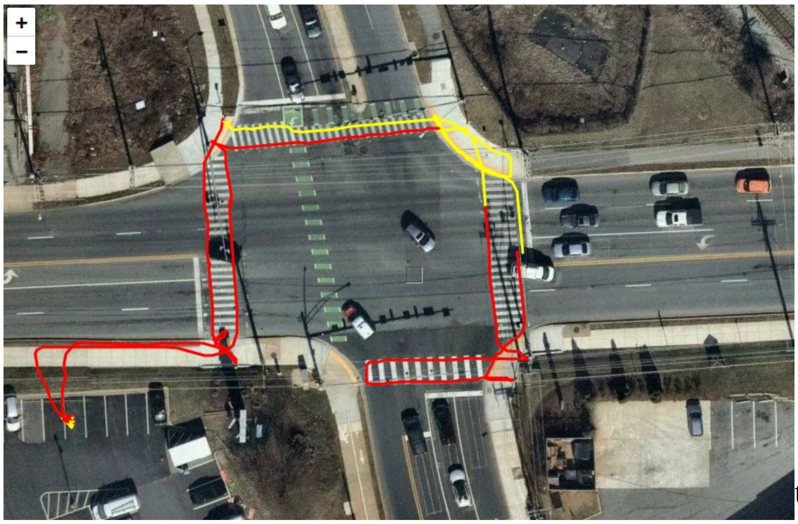
The design module launches a genetic algorithm competition process for each intersection defined in the system. A master overseer process will take results of each intersection competition and feed it back into a solver to optimize for safety, cost and social equity.

ES-CMA was used to dominate the Robo Cup challenge for a number of years. It require up to a couple of days to run on a cluster super computer to generate new soccer playing behaviors.

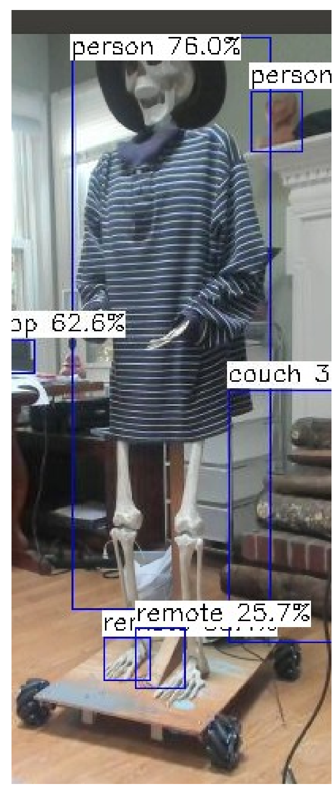
Optimizing just one intersection is of comparable complexity of the soccer GA run. To do this for a hundred or 10,000 intersections and run that in a nest loop trying optimize the entire agency ISS spend, will require computing power capable of solving NP-complete problems.

The design optimizer is expected to behave non linearly. For instance, a social equity ground state setting of equal number of crashes in low and high income neighborhoods could result in large spends on low income intersections while high income intersections experience. We will use generative design to converge on the funding distribution solution maximizing social equity and minimizing crash and crash severity.

Our system will run evaluation testing of all sensors, alert devices and system, AI models, under an array of road conditions. This performance data is captured in a large number of 3D point clouds. Each series performance points for each performance related characteristics..   This data then becomes the solver/optimizer input.



RTK GPS trackers to provide a ground truth to compare to sensors data from sensor under test.



We have several autonomous mobile platforms that can move mannequins around to simulate pedestrian, scoter and bike traffic. We also have large drive system to fabricate vehicle facades to simulate vehicle traffic.

Infrastructure based audio and visual warning messages and alerts are similarly optimized as are sensors for selection, placement and heading of signs, signals and speakers.

Rather than propose a square “peg” solution suited to just operate on US DOT’s test intersection define in this completion, CCA will provides just the right shape “peg” custom fit for each intersection:

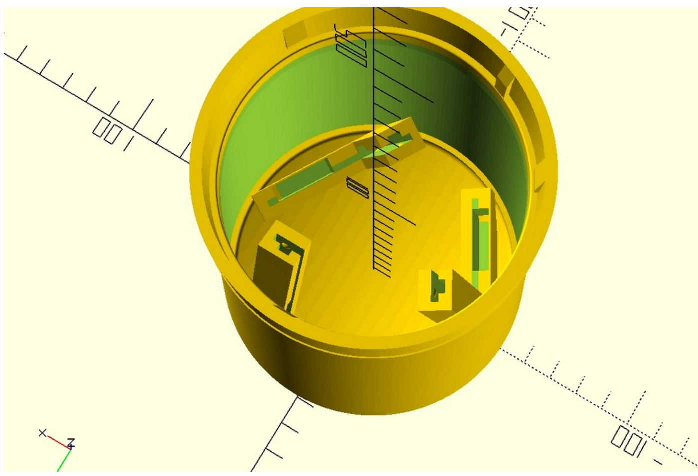
Deployment

First step of this module is to to automate capture 3D mesh of the intersection, overlaid with cad wire frame of intersection's infrastructure defining where sensors can be mounted and power can be accessed.

Once the design module has solved for sensors types and quantities, placement at on available infrastructure with power, sensor heading, height and angle, the deployment module creates a bill-of-materials manifest and detailed installation instructions.

For each sensor to be deployed the system 3D prints and installation tool that secures to the sensor in only one alignment. This tool has a RTK GPS receiver, digital compass and laser range finder to a automate accurate placement, heading and angle of sensors.

To reduce or eliminate the need for mount hardware, we have a programable cad system that generates sensor enclosures custom designed for each placement site to match the sensor orientation in the design.



Site customize 3D printed smart street light controller enclosure with 3 UWB sensors brackets

It is necessary for the system to have precision placement and matching sensor configuration to achieve accurate translation of road objects from the camera's flat image pixel position, to GPS coordinates, 3D Cartesian and UTM coordinates(LIDAR).

These settings are recalibrate once the sensors are installed and operating using alignment match algorithm that registers the sensor network onto the previously geo-registered 3D digital twin mesh of the intersection and an aerial map.

We already have software that can translate sensor network configurations at one site to a different site.

We used software to set up a closed course replica of a pilot intersection site in a large city.

Operations

The operations module will use AI to dynamically optimize the sensor data fusion of the sensor network for an intersection.

Each sensor-road object pairing in the intersection, will have a weight that is drives the fusion algorithm. Those weights will be dynamically recalculated at at least 10Hz, using various AI models, spatial-temporal data, static and dynamics road conditions and road user behaviors.

This optimization is the most computationally demanding one in our platform.

There are many situations that cause object recognition to perform poorly or even fail.

Here are a few examples of problems ond how a dynamic fusion system will make it work.

Problem When objects get too close to each other the merge into one.
Fix whenever two object become oe in the middle of the screen assume you have a crowd and switch to head tracking. If its a vehicle, using make, model and year to pull out a unique feature to train on. Probaly the corners of the roof will be best.

Problem Path trajectories are wobbly.
Fix program check the meta model of relation between intersection and object charteristics that relate to the curretnly running inferece engine. time of day, light level, location to see, etc

Here a just a few of the 4D and other characteristics the alter the weights of sensor data used to fuse with the other sensors.

4D

- Road object distance from sensor
- Periphery of fisheye lens lower performance
- time of day lighting level
- time of day traffic flow
- proximity to tall structures GPS urban canyon effect
- Line of sight & SSD
- Time of year vegetation growth reduced line of sight

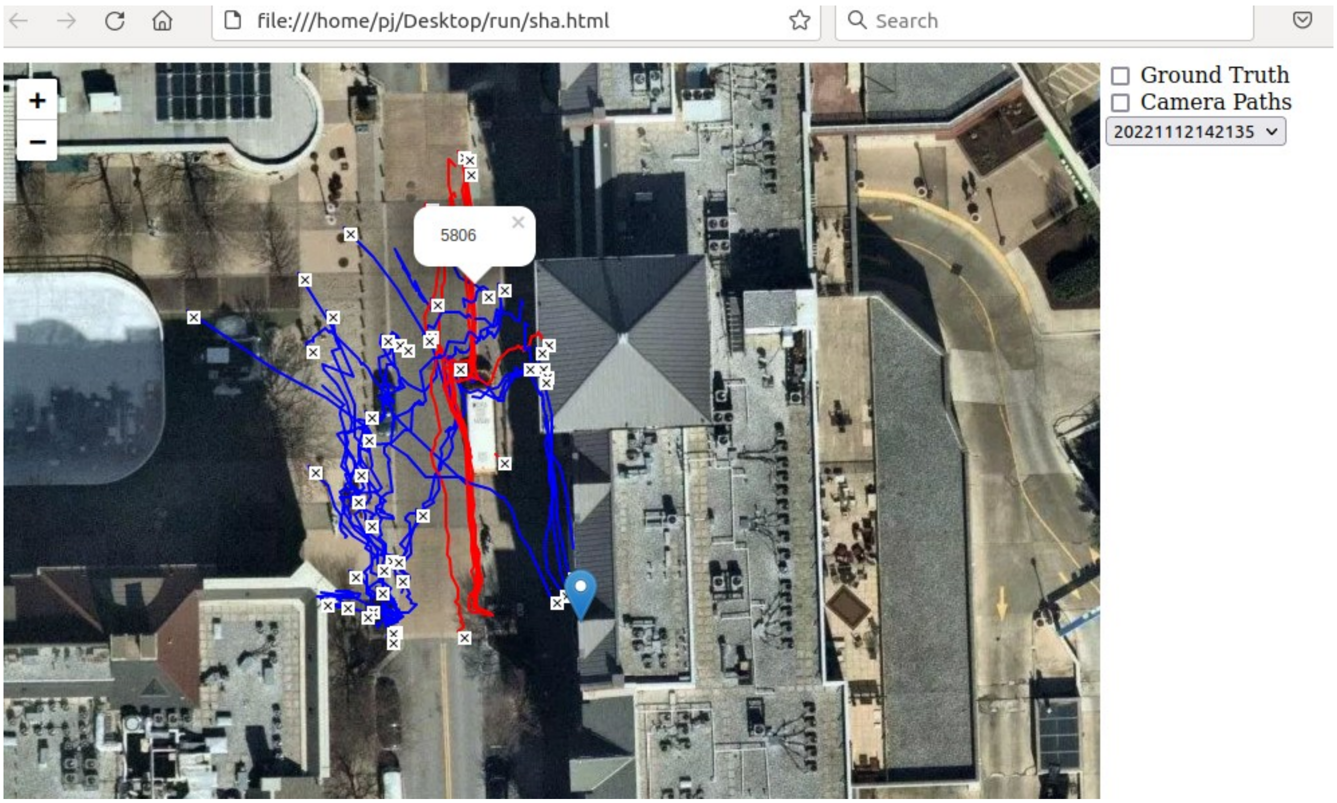
Other

- weather
- lighting
- sidewalks
- speed limits and actual speeding
- number of lanes
- traffic flow
- vehicle weights
- road user path deviation randomness
- road way compliance – crossing against/running lighting

The minimal version of the operations module will run on an intersection road side unit(RSU). Later versions will distribute some of the ISS inference model** defined processing to sensors and other devices. ** A vision inference engine/model is software uses a model trained to recognize a set objects in a scene.

Operations module will support a combination of open sources hardware, software, training models and workflows and vendor “black box” sensors and processes.

We will also be piggybacking on vendor sensors. For example a commercial smart camera with video analytics performs road object detection, classification and segmentation(outlining) and generates GPS location. Our current a parser that extracts ONVIF metadata containing the above data at the video frame rate 7.5 to 60 frames/sec.



Road user tracking with smart camera at Rockville, MD town square. People – blue. Cars – red.

While this data is being used to predict trajectories, we can perform our own Ai vision on the raw video stream to capture the make, model and year of a vehicle which will return vehicle. This in turn can be used to compute stopping times. Which in turn can yield better crash risk and crash severity.

A deep learning model be able to render these solution from a simple calculation of stored kinetic energy, $1/2mv^2$. Some function of Kinetic energy together bumper height might correlate well with crash severity.

Deriving higher level data from micro-positioning

Here is a report of proximity of road users within 6.4 meter of each other at the same point in time.

Test run	object ID	subtype
20221111195512	2608	Car

Object ID	Subtype	Distance	Timestamp
2620	Car	5.7351990719838275	2022-11-12T00:58:20.673Z
2620	Car	4.6368232541521115	2022-11-12T00:58:20.745Z
2620	Car	4.504256909485549	2022-11-12T00:58:20.805Z
2620	Car	4.136950888525771	2022-11-12T00:58:20.872Z

Position data overtime creates a direction and velocity vector to predict future paths and probability of crashes and near misses.

Add in vehicle weight(mass) and you get a momentum vector that can be related to crash severity.

As previously stated a can identify a path randomness volatility for each road user and project a cone shaped heat map of probability of future trajectory.

The cone of probability of future travel paths effects the issuance of warning messages and in some cases SpaT signal control messages (ie. elderly hasn't made it across intersection. Extend walk cycle.

A longer wider future path probability will intersect more readily and sooner with other road user's future path probability cones the intersection of these road user cones generates the warning messages and alerts.

It is also feasibility to send I2V messages to "slow down" to high risk vehicles (speeding). It system could also issue I2V control messages to set a maximum speed governor for short periods of heighten crash risk. This could be a legislated requirement like crash bags and seat belts.

Monitor

The monitor module monitors the operation module for proper functions. It uses deep learning to tweak the operations modules data fusion weights to reach better prediction results.

The monitor modules sends outcome data (progress towards ground states target) and near-miss data, to the planning model, improve the risk model output datasets.

Maintenance

The maintenance model will not be implemented for this challenge.

When implemented, the maintenance model will perform AI driven predictive maintenance and send end-of-life predictions to Planning models for replace of failing element with improved element.

This module will generate work orders to replace or repair system elements before they are predicted to fail. The work order process flow will be a function of the Planning-design-deployment system..

Secure Messaging Center

The secure messaging center module will use data models of protocols to driver the transmission and receipt of and handling of messages.

The modules will support at least:

- J2735 message under 5G Cellular V2X
- Onvif metadata for smart camera output
- web and application keystroke and mouse streams for automating sensor configurations
- RTSP video streams
- meta modeled API streams to configure sensors and warning devices
- TCP/IP for integration with smart phones, TSN control center

J2735 messages will utilize WAVE Secure message services. For comminations that can be controlled from both end will will implement a post-quantum cryptography. Camera and other sensors and devices that are “black box” we request an isolated ethernet subnet at the test site.

The proposed system will implement a 5G cellular Magma type isolated cell mode for the C-V2X communications.

Sensors

Currently, our ISS generator platform supports:

- Onvif compliant cameras and lidars
- RTK GPS base and rover – also used as ground truth system
- UWB

Some of the off-the-shelf sensor technology will will be including are:
- stereo and depth cameras
- J2735 basic safety message(BSM) from connected vehicles
- Millimeter wave imaging radars
- cell phone MAC address sniffers
- pulse radars
- IR camera’
- ultrasonic range finder
- proximity sensors

We will be implementing an open source AI vision camera sensor for regular and low light cameras using Yolo8 software.

One improvement to what appears is to using a “clean plate” empty background to subtract all but moving object from the scene prior to running the Deep learning(DL) inference engine on the image.

We will fuse positions returned by multi-camera and sensors. The risk analysis AI should identify which sensors are complimentary too each other. ie. one performs well when the other sensor perform poorly. Under variable weather and light conditions.

Most Ai cameras provide a confidence level of the object classification between 0% and 100%. We will also be adding confidence levels to detection(false positives), segmentation(outlining), trajectory, crash and crash severity prediction.

In order improve the reliability of open source vision we will be training DL models:
- with 3D backgrounds and objects.
- with short series of video frames instead of single images

- using synthetic training (fast low cost training) to train for multiple permutation of characteristics
  and more

Warning messages

The system will support both connected and on-connected road users.

We won’t be modifying how messages received by connected vehicles are handled.

We will develop iPhone and Andriod apps to audio, vibration and visual alerts and warning messages.

In addition to common dynamic signs and beacons, the system will prototype a laser projector to highlight vulnerable road users hidden in dark shadows.

Ising Physical Solver

In order to dynamical optimize road user micro-locations, trajectory, crash, near-miss and crash severity at at least 10hz, a processor is need to solve NP-completer problems. We believe the only viable solution is utilizing coherent ising machine at the intersection(edge).

Quantum annealers like to the DWAVE machine are sparsely connected, which limits the type of problems that can be easily solved. Degenerate Optoelectronic Parametric Oscillator Ising machines are “all to all” coupled. And have been made with 100,000 “spins”,

Given a 10 year horizon to reach scale, we are confident coherent Ising Machine will available at under $1,000.

The system produced for this challenge will at a minimum demonstrate. The NTT 100,000 spin DOPO machine uses a 5 kilometer long fiber ring to hold the 100,000 spins.

We will attempt to borrow an Ising machine or get a limited license to build one of for this project.

Otherwise, we will implement a proof-of-concept implementation of a Coherent Ising machine simulation on a conventional CPU/GPU machine to solve a normalized/flatten problem set. Similar to Ising-Traffic project[2].

On phase 1A funding we will cost out the effort to build a bench top DOPO Ising machine and a lower cost board level optoelectronic integrated version.

Test Site requirements

If we make it that far, our biggest ask for the test site is that it be open sky. So we can use RTK GPS as the ground truth for training and testing the AI and for fitness testing genetic algorithms.

The second ask would be for a fairly flat intersection. This will flatten the problem, requiring less compute power. This means low power and

Team

Crystal Clear Automation, LLC - Team Lead

Crystal Clear Automation is a Maryland R&D Ag-Text business.
CCA has been applying its technology on several transportation projects beginning two years ago.
Our main focus in achieving vision zero, by design.

Peter James –General Manager Crystal Clear Automation, LLC

Peter is the chief architect of the system. Peter has a 50 year carrier in managing development teams in developing complex systems. Peter developed the first distributed database, master production schedules, factory flor control systems, broadband testing system, large real-time logistics systems.

For the last 20 years Peter has develop an array of integrated automation, robotics, sensors and i/o systems.

In 2020/21 Peter developed a smart crosswalk testing database driven platform that automated testing of smart crosswalk vendor technology.

This year Peter developed a pilot demonstration of iPhone ultrawide (UWB) micro-positioning.

Sanjay Ranka – Computer Scientist

Sanjay Ranka is a Distinguished Professor in the Department of Computer & Information Science & Engineering at the University of Florida.

Sanjay’s research in high-performance computing and big data science is an important avenue for novel discoveries in large-scale applications. The focus of his current research is the development of efficient computational methods and data analysis techniques to model scientific phenomenon, and practical applications of focus are improvements to the quality of healthcare and the reduction of traffic accidents.

Nathan McNeil - Transportation Research and Education Center
Portland State University

Nathan McNeil is a Research Associate at the Transportation Research and Education Center (TREC) at Portland State University. He conducts research on bicycle and pedestrian safety, infrastructure and equity, along with emerging and shared mobility, community engagement and travel behavior. He was principal investigator on recent national studies of bike share equity, including providing information and resources to cities and system operators on how to develop and run equity programs (National Scan of Bike Share Equity Programs). Other recent research has included evaluating programs to improve mobility options for low-income Portlanders, and understanding factors associated with pedestrian safety and social equity (Understanding Pedestrian Injuries and Social Equity). He has also worked to develop research and guidance, including contributing to developing the 2021 Research Roadmap for AASHTO's Council on Active Transportation, the Federal Highway Administration's Strategic Agency for Pedestrian and Bicycle Transportation (2016), and the Federal Transit Administration's Manual on Pedestrian and Bicycle Connections to Transit (2017). His research into active transportation safety includes developing a Guide to Pedestrian Analysis (2022), and ongoing work on bicyclist safety at roadway segments (NCHRP 15-74) and intersections (NCHRP 15-73).

References

[1] Solving 3D Coverage Problem using Genetic Algorithms in Wireless Camera-Based Sensor Network Modeling - https://ieeexplore.ieee.org/document/9072874

[2] Ising-Traffic: Using Ising Machine Learning to Predict Traffic Congestion under Uncertainty - https://ojs.aaai.org/index.php/AAAI/article/view/26121