Interstate-24 MOTION: Closing the Loop on Smart Mobility

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***Abstract*—We introduce the I-24 Mobility Technology Interstate Observation Network (MOTION), a transportation cyber-physical systems testbed under development in Tennessee. It consists of a six-mile freeway segment instrumented with 400 4K resolution cameras, processed by a real-time compute system to enable continuous performance monitoring of freeway traffic. The testbed is being developed to support next generation connected and autonomous vehicle technologies and advanced traffic management. When complete, the testbed will be the longest continuously observed freeway segment in the world. This article introduces the testbed, discusses the core design choices, and outlines the preliminary work conducted to support the design.**

***Keywords*-object tracking; sensor deployments; transportation cyber-physical systems;**

I. Introduction

New sensing, communication, and control technologies are enabling a digital transformation of transportation systems. As an illustrative example, one of the major technological innovations enabling this revolution is the realization of *connected and autonomous vehicles* (CAVs). The majority of the best selling cars in the US are now equipped with *Society of Automotive Engineers* (SAE) designated level 1 or level 2 automation systems. These driver-assist systems control the vehicle differently than human drivers, opening up possibilities to alleviate "phantom traffic jams" that are a result of human driving behavior. Even a few CAVs mixed in regular traffic can dramatically reduce fuel consumption of the overall vehicle flow [1]. Next generation systems will integrate infrastructure assets and individual vehicle control systems to jointly manage traffic flow [2]. This will necessarily raise the need for freeway monitoring systems that can accurately monitor the impact of individual vehicles on overall traffic flow.

Unfortunately, such powerful tools are double-edged. In some cases, technological innovations proposed to solve one mobility problem can actually exacerbate issues in mobility systems as a whole. For instance in [3], [4], it was shown that many currently commercially available *Adaptive Cruise Control* (ACC)-equipped vehicles, while increasing the driving comfort for a single driver [5], amplify perturbations and cause downstream instabilities in a traffic flow. Likewise, [6] proffer using simulated experiments of *platoons* of trucks that such a driving strategy can negatively impact the merging efficiency and overall safety of the surrounding roadway.

These examples clearly illustrate the need for high-fidelity open-road testbeds where emerging transportation technologies can be observed and assessed, particularly to determine the positive and negative emergent phenomena when deployed in real traffic environments. Yet it remains extremely challenging to collect real-time mobility data on open roads, both with enough fidelity, and enough scale, to identify and assess such effects.

Motivated by the above needs, in this article we introduce the *I-24 Mobility Technology Interstate Observation Network* (MOTION), which is a densely instrumented freeway that enables continuous, ongoing coverage of a roadway at the fine-grained vehicle trajectory level. MOTION consists of a network of 400 pole-mounted 4K resolution cameras recording video data that covers a six mile stretch of freeway in its entirety. The raw video data stream exceeds 130 TB/day of traffic data footage that must be processed in real-time to extract precise vehicle locations, trajectories, and other relevant information from the entire monitored portion of roadway. Data is reported for each of the 180,000 vehicles per day that travel on the roadway throughout the full length of the instrumented freeway. An illustration of the concept is shown from the first MOTION prototype pole located at the I-24/I-40 interchange shown in Figure 1. We are now installing eighteen cameras on three poles covering 1800 feet of roadway, with full system completion expected by the end of 2022.

The main contribution of this article is to introduce the MOTION testbed, which is designed as an open-road transportation *cyber physical systems* (CPS) testbed. The core innovation of MOTION is the ultra-dense deployment of 4K resolution video cameras that are processed in real time to generate continuous vehicle trajectories on an open freeway. We detail motivating considerations in the design of such a system, and we present our preliminary experiments

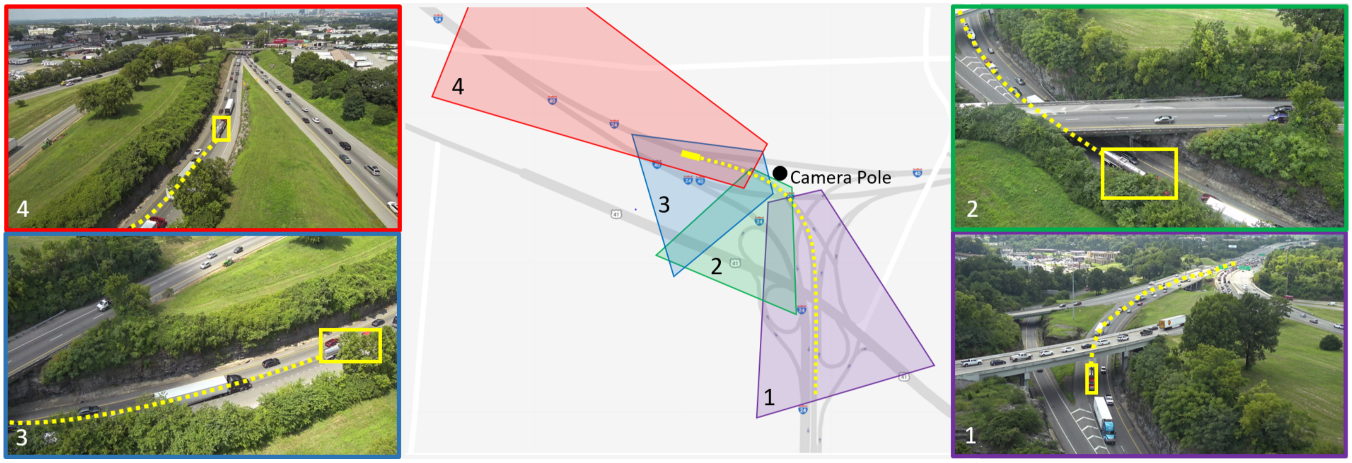

Figure 1. I-24 MOTION prototype installation. Multiple overlapping 4K cameras enable tracking vehicles seamlessly along the roadway.

assessing the feasibility of the system, conducted as part of the first phase of the MOTION deployment.

The remainder of this article is organized as follows. In Section II, related testbeds and experiments for analyzing mobility systems are assessed. In Section III, we present major design considerations of MOTION and discuss our approach for dealing with the challenges of large-scale sensor deployments for traffic observation. Section IV details our initial tests to validate the feasibility of this system, and Section V concludes the article by identifying areas of future work.

II. Background

In this section we briefly introduce the concept of trajectory data, review major projects in traffic sensing technologies, and review the state of the art freeway testbeds for transportation CPS.

A. Trajectory Data

The main challenge in understanding broad system-level properties in mobility such as overall energy efficiency, safety, or flow stability is that these properties depend on the driving characteristics of all vehicles in a traffic stream, and each vehicle must be analyzed to a very fine level of detail. *Trajectory data*, or absolute positions of each vehicle at regular time intervals, is considered the gold standard for data collection. High-quality vehicle trajectory datasets support research on traffic flow theory [7], driver behavior modeling [8], and many other topics [9]. Unfortunately, such datasets are hard to come by and are limited both in length and duration. For this reason, developing reliable, extensive methods for collection of trajectory data is viewed as one of the largest challenges for continuing traffic flow research [7].

B. Major Traffic Sensing Projects

Historically trajectory data collection relied on cameras to view a large portion of a roadway at once. In the 1970's, [10] utilized a helicopter-mounted camera and image processing to extract trajectory data explaining the formation of traffic waves. In the early 2000s, the *System for Assessment of the Vehicle Motion Environment* [11] introduced a portable system of cameras rigged on mast-poles to extract trajectory data. Despite the novelty of this concept, its use never extended far beyond initial feasibility tests which covered 600 feet of roadway for an afternoon. In 2004, the seminal *Next Generation Simulation* (NGSIM) project used building-mounted cameras to gather trajectory data for several 15 minute datasets spanning several hundred feet on two freeways in California [12]. The most recent trajectory dataset, known as the *Highway Drone Dataset* (High-D), contains a total of 16.5 hours of trajectory data at 16 different locations, each approximately 400 meters in length, making this dataset an order of magnitude larger than its predecessor NGSIM [13].

Despite the importance of trajectory data, other traffic sensing technologies are much more widely deployed. For example, California's *Freeway Performance Measurement System* (PeMS) system was developed to clean and distribute inductive loop detector data collected throughout the state [14]. The Mobile Century project introduced the concept of smartphone based traffic monitoring [15], which is now widely adopted by navigation companies globally.

C. Existing Open-Road Testbeds

A number of ongoing programs for traffic data and research exist on open roads. The Northern Virginia Connected Vehicle Testbed, launched in 2013, uses *Dedicated Short-Range Communications* (DSRC) devices as well as cell-network communications to record approximate vehicle locations along several major stretches of interstate to inform real-time traffic management systems [16]. Similarly, the California Connected Vehicle Testbed uses DSRC for communication between DSRC-equipped vehicles and infras-

Vehicle Data System	Vehicle Counts	Fine Trajectories	Seamless	< One Mile	Ongoing
PeMS	Yes	No	No	Yes	Yes
Mobile Century	No	No	Yes	Yes	No
NGSIM	Yes	Yes	Yes	No	No
HighD	Yes	Yes	Yes	No	No
MTO	Yes	Yes	No	No	Yes
N. VA Testbed	No	No	No	Yes	Yes
CA CV Testbed	No	No	No	Yes	Yes
ACTION	Yes	No	No	Yes	Yes
I-24 MOTION	Yes	Yes	Yes	Yes	Yes

Table I
COMPARISON OF VEHICLE DATA SYSTEMS.

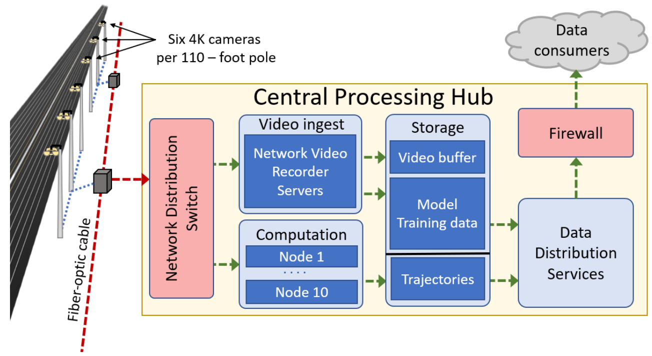

Figure 2. I-24 MOTION system overview.

tructure to enable greater efficiency in driving behavior and infrastructure operation. [17]. The ACTION testbed, slated for completion in 2022, will provide an extensive camera system covering much of Tuscaloosa's roadway network for more effective incident management and demand-adaptive mobility decision-making [18]. The Minnesota Traffic Observatory's Beholder system uses traffic cameras and a suite of other sensors to provide partial trajectories on a dangerous interstate interchange [19].

Table I provides a summary of the capabilities of historical and current mobility data systems. The identified shortage of vehicle trajectory data motivates our implementation of a large-scale vehicle observation testbed. While each system offers benefits and useful data for traffic operations, none offer real time, seamless, large scale trajectory data needed to support transportation CPS development.

III. System Architecture

In the following subsections, we discuss major decisions and motivating factors in the design of I-24 MOTION with respect to the type and number of sensors deployed, the computing regime (central versus edge), and the processing pipeline used to convert sensor readings into trajectory data. Figure 2 provides a high level overview of the system networking, hardware and storage components. A video ingest in the central processing hub stores video in a rolling buffer while computation nodes process the data stream in real time.

A. Sensor Components

Sensors for vehicle trajectory data collection are selected according to spatial and temporal resolution as well as ruggedness. Sufficient spatial resolution is required to localize a vehicle within approximately one foot of its absolute position to provide high-quality trajectories. A temporal resolution of 10 Hz is required to capture high-speed changes in traffic conditions such as extreme braking events, as defined based on [12]. Sensors are also required to be rugged enough to withstand normal and severe weather conditions such as heat, ice, and water for an expected operating lifetime of five years. Based on these constraints, two main categories of sensors are considered for I-24 MOTION:

- *Light Detection and Ranging (LIDAR) Scanners* - Laser distance scans are used to capture geometric information about a scene with high resolution. Current models provide readings at 15 Hz and capture information at $0.1\,\mathrm{deg}$ intervals.
- *Cameras* - Current 4K resolution sensors capture complete visual information from a scene at 30 Hz and at $0.028\,\mathrm{deg}$ intervals (2160 pixels over a 60-degree field of view).

Cameras are ultimately selected for the I-24 MOTION. At present, LIDAR units are an order of magnitude more expensive than 4K resolution cameras suitable for traffic monitoring. Cameras preserve color and lighting information, which will aid in vehicle re-identification and other data analyses besides trajectory extraction; LIDAR does not. Cameras provide higher resolution than current LIDAR models and cover roadway at greater distances with sufficient resolution. Lastly, cameras have been used in traffic operations for over 20 years, so are well-proven as a traffic monitoring solution, whereas LIDAR units are not traditionally used for long-term fixed traffic monitoring installations. Unlike LIDAR, which has good performance in day and night time conditions, a challenge for cameras is that the performance can deteriorate in low lighting conditions.

B. Infrastructure Components

The precise placement of camera poles along the roadway will greatly impact the resolution and completeness of the data collected. Ideally, poles should be tall enough to provide an un-disrupted viewpoint of the roadway. However, logistical and cost considerations limit the pole height to 110 feet, and all poles must be located on one side of the freeway. Thus, four main considerations inform camera placement:

- *Perpendicular Occlusion* - Vehicles in a lane closer to the camera can *occlude*, or block, vehicles in lanes farther from the camera. This type of occlusion occurs perpendicular to the roadway, in which direction vehi-

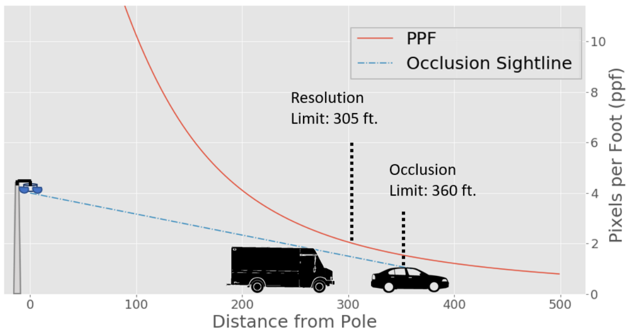

Figure 3. Parallel occlusion and resolution limit diagrams.

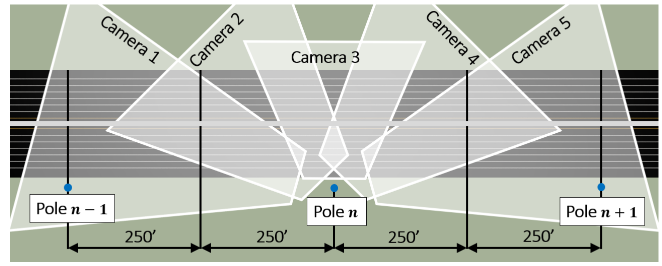

Figure 4. Camera field of view alignments for complete roadway coverage.

cles are spaced approximately 12 feet apart on center in standard width lanes.

- *Parallel Occlusion* - Tall vehicles sufficiently far from the camera can occlude short vehicles travelling in front of them. This type of occlusion happens in sight-lines roughly parallel to the roadway, in which direction vehicles may be closely spaced in slow-moving traffic.
- *Resolution* - Cameras and LIDAR sensors both provide constant angular resolution, but this angular resolution covers an increasingly large distance along the roadway at locations farther from the sensor. To enable both accurate vehicle detection as well as to enable a variety of other use cases, a minimum resolution of 2 pixels per foot along the roadway is required. This means that a section of road from d to $d+1$ feet from the camera must have at least 2 pixels covering it in the direction parallel to the roadway.
- *Field of View* - A sufficient number of cameras must be placed such that their fields of view cover the entire roadway and also overlap.

Though some state-of-the-art object detection algorithms provide sub-pixel accuracy, a larger margin of error is added to account for algorithm inaccuracies and detection difficulties for I-24 MOTION. Camera placements are calculated to provide a minimum 2 pixels per foot along the roadway using a straightforward calculation. Perpendicular and parallel occlusion limits are calculated to determine whether all lanes will be free from perpendicular occlusion and at what distance parallel occlusion will become a limitation. Standard vehicle dimensions and spacings are used, and vehicles less than 50% visible are considered occluded. For calculations, we assume a de-rated pole height of 100 ft to account for varying terrain elevations adjacent to the roadway. From these constraints, we find that a 4K (3840 x 2160 pixel) resolution camera can provide 2 pixels per foot along the roadway up to 305 feet from the pole. Based on resolution and occlusion constraints (resolution governs as seen in Figure 3), a conservative coverage radius of 250 feet is selected for each pole.

Field of view calculations are carried out along the freeway via a 3D model to ensure sufficient cameras are mounted at each location to provide complete coverage of the entire radius of coverage along the roadway. Based on the roadway width for the I-24 MOTION, it is determined that at least five cameras per pole are necessary to provide sufficient coverage of the radius of coverage. Figure 4 shows the resulting configuration.

C. Computing Regime

To extract trajectories from the video data, we consider both a centralized processing approach and an edge computing approach. Recently, edge computing has been a popular choice for IoT mobility sensor applications [20], [21]. I-24 MOTION will have roughly 400 4K cameras when completed. Using H.264 compression, a conservative estimate for the network bandwidth requirement is 15 gigabits per second (GBps). Edge processing reduces network bandwidth requirements, which can be favorable if the network bandwidth is limited (for example on a cellular network). If raw data contains *personally identifiable information* (PII), edge computing can be used to strip the data of PII. Moreover, decentralized approaches can improve system robustness by eliminating single points of failure of the computing resources.

Despite these advantages, most edge computing solutions are limited in terms of *graphics processing unit* (GPU) computation performance compared to centralized computing solutions. The object detection algorithms in I-24 MOTION must run in real time (at the rate at which data is produced by cameras). It is possible that specialized edge compute resources can maintain high frame-rates at lower resolutions and when there are few objects in the frame [20], or by intelligently sharing on and off-edge compute resources as in [22]. Thus, in I-24 MOTION we adopt a centralized computing paradigm. Moreover, co-locating all of the computational resources allows us to dynamically reallocate compute resources to manage workload and scale the computing needs as more algorithms are deployed to extract additional information from the videos. I-24 MOTION is located concurrently with a pre-existing optical fiber network installed by the Tennessee Department of Transportation for intelligent transportation system applications which supports

40 GBps of traffic, a suitable private network for data transfer.

D. Software Components

The software processing pipeline must reliably and accurately convert camera data into vehicle location data. Object detection, tracking, and trajectory conversion algorithms must run in real-time with respect to the input rate to enable the camera network to operate continuously for a long-term deployment. We assume that small inaccuracies and fluctuations in readings, as well as temporary losses of a vehicle's location, can be smoothed and corrected in post-processing steps.

1) Vehicle Detection Algorithm: For I-24 MOTION, *object detection* algorithms are used to extract vehicle positions from camera image data. The task of object detection is well explored, and mature algorithms exist for efficiently detecting objects. For example, YOLO-v3 [23] and Faster R-CNN [24], are two state of the art object detection algorithms. Both algorithms are based on the use of *convolutional neural networks* for extraction of high-level information from image pixels; the main difference is that Faster-RCNN relies on a two-stage detection framework in which rough detections are first output, and then this set of detections is used to create a second, more refined set of final predicted object locations. YOLO, on the other hand, relies on a single prediction stage, making it faster but slightly less accurate. In this work a pre-trained YOLO-v3 model is used for object detection.

2) Tracking: Object tracking is the task of locating the same objects in consecutive frames of video data. For I-24 MOTION, a *tracking by detection* approach is employed, in which object detection is performed on every frame, and subsequently detected objects are matched between frames. Several accurate algorithms for object tracking exist based on modeling object types and behavior [25], filtering [26], and direct output from neural networks [27].

The *Simple Online Realtime Tracking* (SORT) algorithm [26] is used for tracking for its low computational overhead and high accuracy. It uses a Kalman filter to predict and correct the positions of each vehicle over time [28].

To implement SORT, the state of each vehicle:

$$\mathbf{x}_n = [x_n, y_n, s_n, r_n, \dot{x}_n, \dot{y}_n, \dot{s}_n]^T, \qquad (1)$$

is expressed as a 7-dimensional state vector where x and y denote the bounding box center coordinates, s is the width of the bounding box, r is the width-to-height ratio of the bounding box, and $\dot{x}$, $\dot{y}$, and $\dot{s}$ denote the rate of change of x and y. A constant velocity model is assumed resulting in a state space model (presented here for a single vehicle) of the form:

$$\mathbf{x}_{n+1} = \mathbf{F}\mathbf{x}_n + w_n \,, \quad \mathbf{y}_n = \mathbf{H}\mathbf{x}_n + v_n, \qquad (2)$$

where $\mathbf{x}_n$ denotes the state at timestep n, $w_n \sim \mathcal{N}(0, \Sigma_w)$ is the process noise, $\mathbf{y}_n$ is the measurement at timestep n and

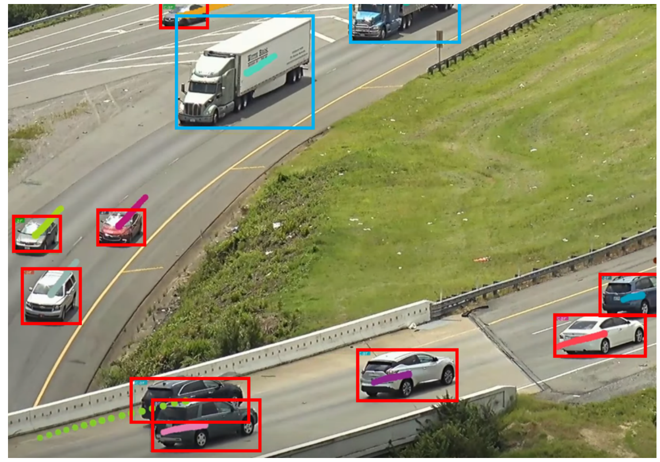

Figure 5. Vehicles tracked with YOLO and SORT. Red boxes denote cars, Blue boxes denote trucks. Point trails denote the position of the associated vehicle in prior frames.

$v_n \sim \mathcal{N}(0, \Sigma_v)$ is the measurement noise. The dynamical model $\mathbf{F}$ and the observation model $\mathbf{H}$ are written explicitly as:

$$\mathbf{F} = \begin{bmatrix} 0 & 0 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \mathbf{H} = \begin{bmatrix} 1&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0 \\ 0&0&1&0&0&0&0 \\ 0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0 \end{bmatrix} \qquad (3)$$

where Δt is the time between consecutive video frames. The system (1) is observable and thus can be accurately estimated with a Kalman filter according to the update and measurement equations (2). Other state spaces and model dynamics were also considered but were found to perform worse.

An important detail in the tracking problem is the assignment of detected objects to the correct vehicle in the state space. This is done by matching the predicted positions in the model prediction step of the Kalman filter to the actual detected objects from the object detector, using the Hungarian algorithm for bipartite matching [29]. Once the assignment is known, a standard Kalman update can be performed to correct the predicted state based on the measurement. Figure 5 shows the use of this method for tracking object trajectories through consecutive frames of video from a test of I-24 MOTION.

3) Trajectory Conversion: To be useful for intelligent mobility applications, tracked object trajectories must be expressed in absolute coordinates, rather that image space coordinates. Assuming that the ground plane is flat, there exists a *perspective transform* expressible as a $3x3$ *homography matrix* that maps points from the image plane to the ground plane while preserving straight lines. If four points in image space and their corresponding ground plane points are known, a straightforward system of linear equations can be solved to determine the 8 parameters of the transform $a_{11}, \cdots, a_{32}$ (by convention the last parameter is always 1). Then, an arbitrary image plane point (x_n, y_n) can be mapped to its corresponding ground plane point (x', y') via:

$$\begin{bmatrix} i \\ j \\ k \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{4}$$

$$x' = i/k \quad and \quad y' = j/k, \tag{5}$$

where k denotes a scaling coefficient.

E. System Resilience

I-24 MOTION provides robustness to hardware and software failures by way of redundancy:

- *Single Camera Failure* - Cameras are pan-tilt-zoom enabled and six cameras are mounted per pole for redundancy. In case of a camera failure, five cameras can be re-positioned to seamlessly cover the area of observation.
- *Single Pole (Networking Hardware) Failure* - Cameras on neighboring poles have overlapping fields of view and can cover the area of the failed pole (with possible occlusion).
- *Single Compute Node Failure* - Load balancing can redistribute computational load to other compute nodes. If available compute resources cannot keep up with data influx, the frame resolution can be reduced to speed up the computationally expensive object detection step.
- *Storage Failure* - Data is stored at multiple locations and can be restored to failed location after the failure is addressed.

IV. Feasibility experiments

Preliminary experiments have been carried out to verify the feasibility of the proposed sensors, physical infrastructure, and computational pipeline. Data is collected from a single six-camera pole for one week from August 9-16, 2019. This data is then processed with the pipeline described above to produce a trajectory dataset. To enable tests with six cameras per pole, a custom mounting bracket and associated networking hardware was also designed, prototyped, and tested (Figure 6). This prototype serves as a feasibility analysis for larger-scale deployment of such a multi-camera mount. Code and videos from the test can be found at http://github.com/DerekGloudemans/I24-MOTION-examples. Thorough experiments will enhance and validate tracking algorithms in our future work.

Figure 6. Multi-camera mount is raised onto 110 ft pole.

V. Conclusion

In this article, we introduce I-24 MOTION which is an open-road testbed designed to support CPS transportation research. We present the overarching design and the preliminary work to date on the prototype hardware and tracking. Our next steps include building a 3-pole, 18 camera network in 2020 and benchmarking the accuracy and run-time of the processing pipeline.

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