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A Region-wide Deployment of an Automated Real-time Truck Parking Availability Detection and Information Dissemination System ⋆

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Abstract: Commercial heavy vehicle-borne freight will continue to be the dominant cross-region shipping mode for materials and goods for the foreseeable future. Federal hours of service (HOS) regulations mandate scheduled minimum times for off-duty and in-transit rest periods to minimize operator fatigue. Without timely, accurate information disseminated to drivers and carriers on where to park, complying to HOS regulations can often become a very challenging task for drivers. This paper describes a region-wide deployment of a unique non-intrusive, multi-camera, truck parking space detection and availability information dissemination architecture. The architecture leverages multi-view Structure and Motion methods to reconstruct a Three-dimensional representation of the environment for estimating unoccupied spatial extents to deduce truck parking availability. Unlike 2D camera sensor-based methodologies, the advantage is its immediate adaptability to a variety of parking facilities and scenarios without the need for any subsequent re-training. The approach also mitigates errors arising from occlusions, and many other environmental conditions that confound many 2D camera-based approaches. The region-wide deployment, operated by a state transportation agency, has been online since early 2019, and has thus far substantiated the technical and day-to-day operational viability of the approach. The performance throughout this period indicates an overall accuracy at or above 90%. This paper provides a general overview of the deployed system architecture and performance characteristics across varied parking facility designs, parking behaviors, and other environmental conditions.

Keywords: Control, freight transportation networks, Traffic Safety, Cooperative logistics, Trip Planning.

1. INTRODUCTION

The amount of materials and goods transported by commercial heavy motor vehicles (CHMVs) is staggering. An estimated 10.93 billion tons— 72.2% of all domestic freight, was shipped by trucks alone in 2021 (Costello (2022))– an increase of 7.2% from 2012. Supporting infrastructure for truck parking is critical. Fisher (2022) summarized a recent 2022 annual Industry-wide survey report that ranked truck parking as the third highest concern by drivers and carriers, behind fuel prices and driver shortages. Regardless of a corridor's truck parking capacity, without timely, reliable truck parking availability information, 83% of drivers spend from 1/2 an hour to an hour, or longer (39%), searching for available parking. The lost time equates to an estimated $7 billion annually in lost wages. They are confronted with the dilemma to continue driving fatigued— perhaps exceeding HOS regulations, to search for available parking, or instead park illegally at hazardous locations, such as freeway ramps and shoulders or other insecure areas (Banerjee et al. (2010), Bayraktar et al. (2012)).

Accordingly, Intelligent Transportation Systems (ITS) technologies have been tested and deployed to provide drivers with real-time truck parking availability along popular truck-borne freight corridors. We developed a novel parking occupancy detection architecture that uses multiple Commercial Off-the-Shelf cameras to construct an accurate 3D structured representation of the viewed environment to perform 3D background subtraction of parked vehicles from the environment to estimate occupancy. Ear-

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lier work initially validated the efficacy of the approach (Cook et al. (2014)). Subsequent pilot studies were conducted to more completely evaluate its field and detection performance at multiple sites in two Upper Midwest states (Morris et al. (2017, 2018)) found the persistent, around-the-clock detected count accuracy to be within ±3 counts 95% of the time to ±2 counts 99.9% of the time, with an overall detection accuracy achieving 93% to 97%. A full scale state-wide deployment of this architecture, managed and operated by the Kansas Department of Transportation (KDOT), has been in operation since early 2019. The geometric designs of most parking facilities do not have delineated parking stalls, and the facility geometries differ significantly from the sites used in the earlier studies. This paper focuses on the required adaptations of the detection and information dissemination architecture for the ongoing KDOT deployment, and the overall system performance across 22 truck parking sites.

2. BACKGROUND

Several technological approaches have been studied (and in some cases deployed) to estimate and disseminate truck parking availability. Trip-wire ingress/egress counting is a commonly used approach to estimate available parking, because this approach can theoretically scale to any sized parking facility. Several sensor technologies have been evaluated and used to implement trip-wire counting. Video (Gertler and Murray (2011)) Microwave Radar, LiDAR (Lopez-Jacobs et al. (2013)), and in-pavement magnetometer sensors (Chachich and Smith (2011), Golias et al. (2018)). One inherent issue with this concept in general, is that even small sensor errors or biases, can accumulate unpredictably over time, requiring regular intervention from human observations to re-zero the counts or re-calibrate the sensors. Direct parking space detection systems, on the other hand, avoid the error pitfalls of indirect approaches. A variety of pavement-embedded wireless battery-powered sensors have been tested and deployed with varying levels of success (Bayraktar et al. (2014), Sun et al. (2018), Haghani et al. (2013)). They perform best for delineated parking stalls that enforce disciplined parking behavior. Installing such sensors disturbs pavement substructures which may create additional maintenance problems over time.

Alternatively, several methods have been proposed that use non-intrusive 2D cameras to detect a multiplicity of spaces. Predominately, they have focused on private vehicle parking. To address diverse scene lighting and occlusion, Huang and Wang (2010) fused a Hidden Markov Model and light model hypotheses to form a probabilistic parking occupancy model for large area car parks, and later developed a learned probabilistic models using projected features defining 'occupied' vs. 'vacant' spaces to infer availability. They used a 3D model shape (3D boxes) prior for each vehicle as part of the generative step to create probabilistic occlusion and shadow maps. Another approach implicitly assumes such a model to develop a feature-based inference model (Huang et al. (2013)). Machine learning models have been designed to classify vehicles from aerial views and occlusion cases, using handcrafted features (Cheng-Feng et al. (2019)), and Generative Adversarial Neural Networks (GANS) to recognize free and occupied car parking stalls (Li et al. (2017)). Padmasiri et al. (2020) proposed a ResNET architecture to perform one-shot detection and location of cars to infer parking spot locations projected in the image through the detection process itself. Bosch GmbH has used their proprietary edge computing embedded camera platform for image-based vehicle recognition to identify parking events within a predefined truck parking stall (Bosch (2022)).

Our approach instead reconstructs a 3D representation of the parking environment using a multiplicity of cameras. The system deduces the spatial parking availability through a 3D background subtraction process. Inherently, the effects from occlusions, shadows, varied environmental conditions, and even occasional view obstructions that occur in the natural environment, all of which introduce challenges to the 2D approaches, are mitigated by the estimated 3D structure of the environment. The detection approach and the current adaptations to further generalize it to more diverse parking behaviors and facility designs are described next.

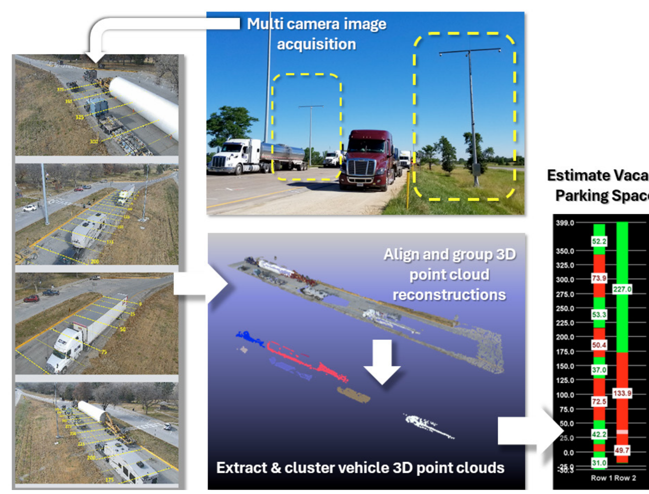


Fig. 1. Multi-camera vehicle detection framework to estimate available truck parking.

3. DETECTION ARCHITECTURE

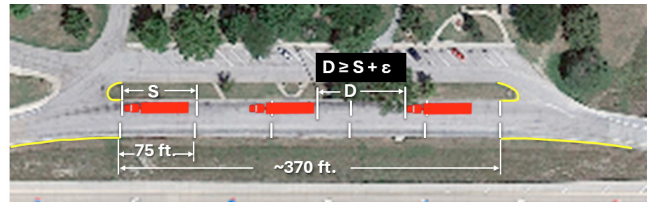
In brief, the detection algorithm is summarized as follows (Refer to Cook et al. (2014) and Morris et al. (2017) for a more detailed discussion of the process). The Bundler software is used to estimate 3D structure and camera motion (Snavely et al. (2006)), using images acquired from a group of three pole-mounted cameras. More succinctly, the Bundler software estimates the full view poses and non-linear intrinsic parameters from a collection of *uncalibrated* camera views, and a sparse set of reconstructed 3D points from the viewed environment (Snavely et al. (2008)). In our case, the camera viewpoint sequence is from similar specification cameras, and therefore conceptually represents a single camera 'in motion' along the same repeated path, for which 3D structure and camera intrinsic and extrinsic parameters can be efficiently estimated (Lourakis and Argyros (2009)). The input to the Bundler is an initial set of putative matching 2D image points from all image pair combinations. SIFT-based image feature matching provides the initial putative 2D matching point set Lowe (2004).

For truck parking detection however, the sparse output set of reconstructed 3D points is insufficient for discriminating parked vehicles from the rest of the scene. Using the output 3D reconstruction points and camera poses from the Bundler, a Patched-based Multi-view Stereo (PMVS) reconstruction software generates a more dense 3D point cloud representation of the scene (Furukawa and Ponce (2010)). The 3 overlapping distinct perspective camera views enforce photo consistency constraints to filter out moving objects, as well as 3D point reconstructions that are inconsistent with neighboring visible surface patches of the vehicles and ground plane. This reconstruction process is repeated many times for different sets of viewpoints to capture the entirety of the parking facility. Note that after this stage, neither the 3D point clouds, nor the estimated camera poses, are scaled and aligned with each other or the physical world, which must be resolved to segment out vehicles 'above' the parking lot surface, and estimate their 3D positions. A calibration procedure using field surveyed points, re-scales, translates, and re-orients each 3D point cloud in order to map them onto the 3D parking lot surface. Corrections to elevation are performed to account for variations in the intrinsic camera parameters, 3D point reconstructions, and the surface topography (Morris et al. (2017, 2018)). The 3D points 'above' the parking lot surface and within parking stall boundaries are then segmented out, and used to classify occupancy (Cook et al. (2014)).

3.1 Continuous Free-Space Parking Availability Estimation

The described algorithm process was developed and tested for facilities with marked parking stalls. However, most KDOT truck parking areas provide continuous parking lanes instead of marked, designated parking stalls. This type of vehicle parking, is referred to as 'undisciplined' parking for the remainder of the paper. Such undisciplined parking facility designs are not uncommon in the US. Counting vehicles within these areas typically does not equate to the actual parking space availability. For example, figure 2 illustrates a case of monitoring discrete parking stalls that would underestimate available parking. The approach was adapted to estimate the longitudinal spatial extents of vehicles, as well as free space between vehicles. (Fig. 1) The extents can then determine the adequacy of a vacant space to provide enough clearance for a tractor-trailer CHMV to park. Unsupervised clustering of the merged 3D point cloud (Ester et al. (1996)) separates and identifies the parked vehicles (or other objects). The min-max longitudinally aligned boundary values of the clustered objects are then sorted from entrance to exit, to estimate vacant, unoccupied spaces between, behind, and in front of, vehicles.

Defining a 'vacant' parking space was derived from simulating forward driving pull-in and back-in parking maneuvers with a standard sized a WB-67 tractor trailer with sleeper cab (Harwood et al. (2003)). A commercially available nonholonomic path planning simulation tool that traces tire and vehicle paths (AutoTurn, TranSoft Solutions Inc., Richmond, CA), determined that 90 feet of space is required for the driver to pull out the vehicle from the parking space in the forward direction. When there is unoccupied space between two parked vehicles, 110 feet of clearance is required to allow the truck to back into the spot, and 140 feet of clearance is needed for the tractor-trailer to pull in to park from the forward direction.



(a) KDOT undisciplined truck parking site with 10 spaces

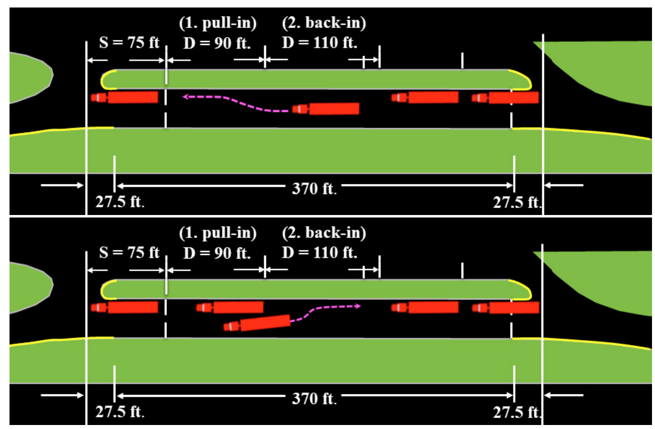


Fig. 2. Sequential truck parking maneuvering scenario within site into 2 vacant spaces.

A 'cooperative' parking scenario was assumed to measure total capacity and parking space availability; entering vehicles always pull forward to the vacant space closest to the egress, in order of arrival (Fig. 2). The first and last vehicles do not require clearance space since under this scenario, there is enough open space either in front of, or behind the vehicle to exit. Parked tractor-trailers between the first and last comply with 90 feet of space so any of them can pull out. The lesser 110 feet of clearance is used for situations with empty clearance space between two vehicles, since a tractor-trailer could theoretically back into such a space. Therefore, 200 feet between vehicles can accommodate two tractor-trailers under the ideal 'cooperative' parking maneuvers (Fig. 2). The behaviors were encoded as heuristics to estimate the 'available' parking for different parking scenarios using the total intended parking space, and the occupied space estimates.

3.2 Sensor Configuration and Site Deployment

KDOT deployed our system architecture to monitor truck parking availability within 22 public rest areas (Fig. 3). In the first year of operation (2019), 18 rest areas along Eastbound and Westbound Interstate 70 corridor (I-70) went online, providing real-time truck parking availability information for 186 public rest area parking spaces between Topeka and the Western Kansas border. In the fall of 2019, the remaining 4 truck parking rest areas along Interstate 135 (two Northbound, two Southbound), North of Wichita containing 44 spaces, were added. Each direction-bound rest area pair is located near the same mileposts across from, or adjacent to, one another. The distance between rest areas is 26.5 to 55.25 miles apart. The undisciplined parking area sites (sites #1-#16, and #19-#22 in Fig. 3) use a turn-out style side roadway to provide two lanes of truck parking, with distances spanning 325 to 525 ft. in length, and roadway widths of 30 to 38 feet. An example of one such site, Junction City WB, is shown in figure 2a.

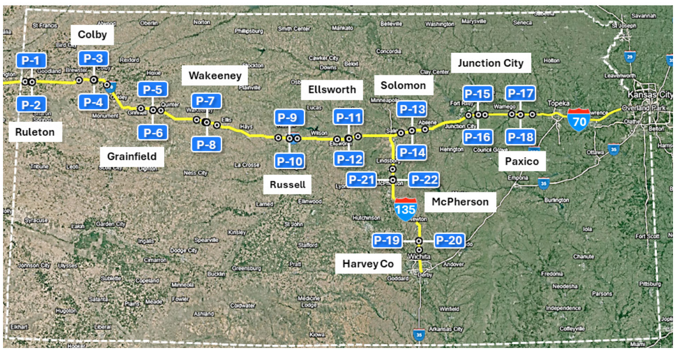


Fig. 3. Truck parking public rest area system deployment. Adjacent markers from rest areas are CMS locations

Using a visualization tool developed in (Morris et al. (2018)), 3D models of representative sites were constructed to visualize vehicle-on-vehicle occlusions and overlay computed stereo disparity angle maps based on proposed feasible camera pole locations, pole heights, and camera positions. Crank-down 40-foot-high camera poles, with a 20-foot wide cross-bar, were specified and manufactured for all deployments (Millerbernd Manufacturing, Winsted, MN). For the free-space parking facilities, two camera poles, with three PTZ cameras, were spaced 120 to 180 feet apart on either side of the truck parking roadway, with the cross bars perpendicular to the parking roadway. The lateral clearance between the poles and roadway ranged from 15 to 20 feet. The disciplined parking sites with delineated stalls, used three camera poles, with one placed approximately in the center of the parking facility, and the remaining two close to each end, with the crossbar perpendicular to the marked stall lines. Four overlapping viewscape patterns cover the needed detection areas of the free-space facilities (Fig. 1).

4. PARKING INFORMATION DISSEMINATION

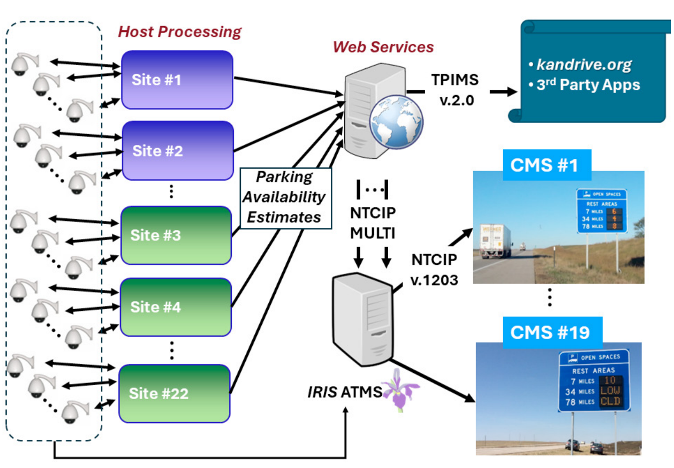


Fig. 4. Overall site parking availability detection accuracy.

The KDOT parking availability status notifications are updated every 4 minutes. A web server aggregates the detection data and camera snapshots and then disseminates the information through three mechanisms. A public traveler and traffic information web portal KDOT (2019) queries the web server to update the parking availability status and corresponding camera images of each site. Second, the web server is queried by a publicly available Advanced Traffic Management System (ATMS) software (MnDOT (2013)) to update a multiplicity of roadside changeable message signs (CMS). Each sign is located 4 to 10 miles upstream of each rest area. The CMS displays the parking availability status of the first upcoming truck parking rest area, and when relevant, the next one (33 to 59 miles) or two (78 to 95 miles) facilities downstream from the first one. Outside private organizations, traveler information service providers, and other public entities can also receive the parking availability status data streams through the TPIMS parking availability communication standard (TOPS Lab (2019)).

5. DATA COLLECTION

The system went 'live' on February 4t̂h, 2019. Midweek (typically Thursday) detection data were harvested for night-time (midnight), early morning (7:30 AM), and mid-day (noon) periods through November of 2023. Ground-truth space vacancy counts have been labeled for 5,860 samples. The observed vacant parking stalls were tallied for the two sites with slanted delineated truck parking stalls (#17 and #18 in Fig. 3). For the undisciplined free-space truck parking rest areas, the beginning and ending distances of each vehicle projected onto the parking area surface were first manually extracted to tabulate the space occupancy extents for each observed vehicle (Fig. 1 shows 4 image view overlays). The spatial truck-parking availability is then estimated using the heuristic rule-based maneuver formulation implemented in the detection algorithm, described in section 3.1.

Table 1 summarizes the variability in parking availability for the number of samples processed from the observed ground-truth labeled samples. Generally, as was expected, the nighttime periods experienced the lowest levels of available parking, followed by early morning, with the highest likelihood of available parking mid-day. Interestingly, the proportion of samples with observed full capacity (no vacant parking space), was relatively small, with between 4% and 8%, with the mid-day period experiencing the highest proportions of full occupancy. The designed capacities by KDOT for each site are indicated within the parentheses next to the truck parking site names in Table 2. Note, however, that what is evident is the broad range of occupancy levels recorded through these periods, which infers a wide range of parking scenarios were used for evaluating performance.

6. RESULTS

Table 2 summarizes parking availability detection accuracy for the undisciplined, and delineated stall truck parking rest area sites, across the time of day periods. The data for a morning period was unavailable for, McPherson NB on Interestate 135, the Night-time data for McPHererson

Table 1. Observed parking availability variations

	Avg.% Capacity	Counts ($\mu \pm \sigma$)	% Full	N
Undisciplined Parking				
Morning	46.17%	4.52 ±2.57	6.83%	366
Mid-day	61.74%	6.17 ±2.36	8.64%	3534
Night	28.53%	2.85 ±2.79	4.10%	1548
Overall	**51.26%**	**5.12±2.91**	**7.86%**	**5448**
Designated Parking Stalls				
Morning	43.48%	6.52 ±2.82	0.00%	44
Mid-day	75.38%	11.31 ±2.21	5.07%	355
Night	13.85%	2.08 ±1.80	0.00%	13
Overall	**70.03%**	**10.50±3.31**	**4.37%**	**412**

SB, and the downstream truck parking facility of Harvey Co SB. Nevertheless, the data indicate the accuracy generally was highest during mid-day (just under 94% mid-day), and the lowest during nighttime periods (92%). Note that the FHWA acceptable minimum accuracy requirement is 85%.

Table 2. Truck parking availability accuracy.

Site (Capacity)	Morning	Midday	Night	Overall
Stall Parking, N=412				
	91.36%	**92.62%**	**92.82%**	**92.49%**
Paxico EB (15)	91.52%	90.04%	93.33%	90.31%
Paxico WB (15)	91.21%	95.16%	92.22%	94.65%
Undisciplined Parking, N=5448				
	92.25%	**94.05%**	**92.01%**	**93.35%**
Colby EB (10)	92.73%	96.76%	95.69%	96.04%
Colby WB (10)	94.29%	94.70%	90.12%	92.62%
Ellsworth EB (10)	93.81%	93.15%	92.40%	92.85%
Ellsworth WB (10)	92.92%	93.26%	95.00%	93.27%
Grainfield EB (10)	95.00%	95.44%	93.99%	94.79%
Grainfield WB (10)	88.26%	93.39%	88.25%	90.74%
Harvey Co NB (15)	87.50%	93.28%	96.67%	93.41%
Harvey Co SB (15)	100.00%	93.75%		93.79%
JuncCity EB (10)	93.33%	95.34%	93.33%	95.08%
Junct City WB (10)	92.38%	93.84%	94.00%	93.70%
McPherson NB (10)		93.38%	90.00%	93.35%
McPherson SB (10)	90.00%	91.68%		91.67%
Ruleton EB (10)	96.00%	93.77%	91.61%	92.98%
Ruleton WB (10)	92.08%	94.34%	92.42%	93.34%
Russell EB (8)	89.20%	93.65%	87.50%	92.94%
Russell WB (8)	92.93%	94.90%	92.31%	94.51%
Solomon EB (10)	91.00%	95.52%	93.33%	95.02%
Solomon WB (10)	92.08%	93.80%	90.91%	93.45%
Wakeeney EB (10)	88.57%	93.46%	92.49%	92.74%
Wakeeney WB (10)	90.83%	93.21%	91.02%	92.09%
All Rest Areas	**92.16%**	**93.92%**	**92.02%**	**93.29%**

A two-tailed analysis of variance of the actual availability count data aggregated for all the sites, indicates that the night-time data tended to under-estimate capacity, and hence *over*-estimate available parking (T = 10.112, CI = [0.2833,0.4197], $\sigma_n = \pm 1.374, N_n = 1562, (p < 10^{-5})$. This is also true for the mid-day time, albeit to a lesser extent $(T = 2.8004, CI = [0.0157, 0.0892], \sigma_{md} = \pm 1.041, N_{md} = 3087, (p = 0.0051))$. However, the morning time sample data did not reveal an under, or over, bias in counting parking availability $(T = 1.8620, CI = [-0.0064, 0.2357], \sigma_m = \pm 1.247, N_m = 410, (p = 0.0633))$. A comparative analysis between nighttime and the morning time $(T = -3.350, CI = [-0.4185, -0.0542], (p < 0.001))$, and the mid-day time $(T = -7.572, CI = [-0.4008, -0.1972], (p < 10^{-5}))$ indicates a modest difference of relative under-count vehicle detection. However, the mid-day samples relative to the morning samples, indicate no significant difference in counting bias $(T = 0.9658, CI = [-0.1043, 0.2286], (p = 0.3346))$. Therefore, a statistically significant, but small overestimate of available parking is more likely to occur at night.

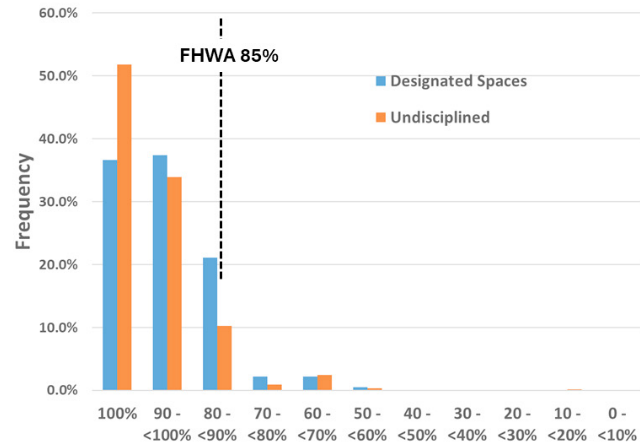


Fig. 5. Overall site parking availability detection accuracy.

Lastly, Fig. 5 shows the composite variability of the detected parking availability estimate across all periods, for the undisciplined, and disciplined (parking stall) truck parking rest areas. Considering the minimum FHWA specified accuracy requirement of 85% for this deployment, the system detection performance, at or above 90% accuracy is exceeded 74% of the time for the designated spaces, and for accuracy at, or above 80% occurs 95.2% of the time. For the undisciplined truck parking sites, the detection performance at or above 90% accuracy occurs 85.7% of the time, and for 80% or greater is exceeded 96% of the time.

7. CONCLUSIONS

A region-wide deployment based on our truck parking detection and information dissemination architecture has been successfully operating for over 4 years, with a persistent parking availability accuracy estimated at 90% or better when compared with the manually observed data. Naturally, the variations in space availability performance were observed across large variations of environmental and parking behavior scenarios, demonstrating general system robustness and viability for providing region-wide truck parking availability. The approach can realign the uncalibrated 3D point cloud data from perturbing factors such as observed pole sway and vibration from wind shear, for example. Challenges persist in expanding the systems to commercial truck parking facilities, where parking capacities can be ten times larger than state-sponsored facilities. Our future research will be directed toward creating self-diagnosis and healing components for the architecture that recognize perspective shifts. These components could be used to trigger an alarm to management to identify problems and perform actionable corrections. Spherical high resolution may be used instead of standard PTZ cameras, which could reduce mechanical problems and improve maintainability.

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