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Development of Rule-Based Safety Checking System for Autonomous Heavy Construction Equipment

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Abstract

The construction and maintenance of highways and roads involve heavy construction equipment, consistently exposing workers to potential injuries and fatalities. A large portion of work zone fatalities could be prevented by automatically detecting objects—including workers—around the equipment, accurately determining their locations, and identifying potentially unsafe situations. The goal of this study is to embed a full situational awareness to construction equipment by adapting vision-based perception techniques. This project developed 1) a process to determine placement of depth cameras and long- range Light Detection and Ranging (LiDAR) on a piece of construction equipment in a simulation insuring the 360-degree visibility, and 2) two sensor-based perception algorithms to detect and track the locations of people and monitor vehicles around the equipment. A field evaluation achieved an average error of 27.1 cm (10.67 inches) in human detection and an average distance-based error 50.1 cm (19.72 inches) in motor vehicle detection within 5m of the construction equipment.

Key Findings

- There is currently no established procedure for helping contractors and heavy equipment manufacturers integrate vision-based sensors into heavy construction equipment to detect unsafe situations.
- We developed a comprehensive framework that allows users to determine “sensor configuration,” including sensor types, sensor placement on the equipment (location and orientation), and sensor programming, tailored to specific work zone conditions and the characteristics of the target equipment.
- The evaluation of the structured procedure demonstrated that it is feasible to use simulation environments to determine the sensor configuration, which can then be successfully implemented in real-world applications.
- The results show that the system achieved full 360-degree visibility and accurate detection of hazards, suggesting that it is possible to surpass the limitations of widely used tag-based hazard detection systems.
- More complex hazard detection logic and advanced alerting methods need to be explored in future research to further enhance the system’s ability to detect and respond to unsafe situations.

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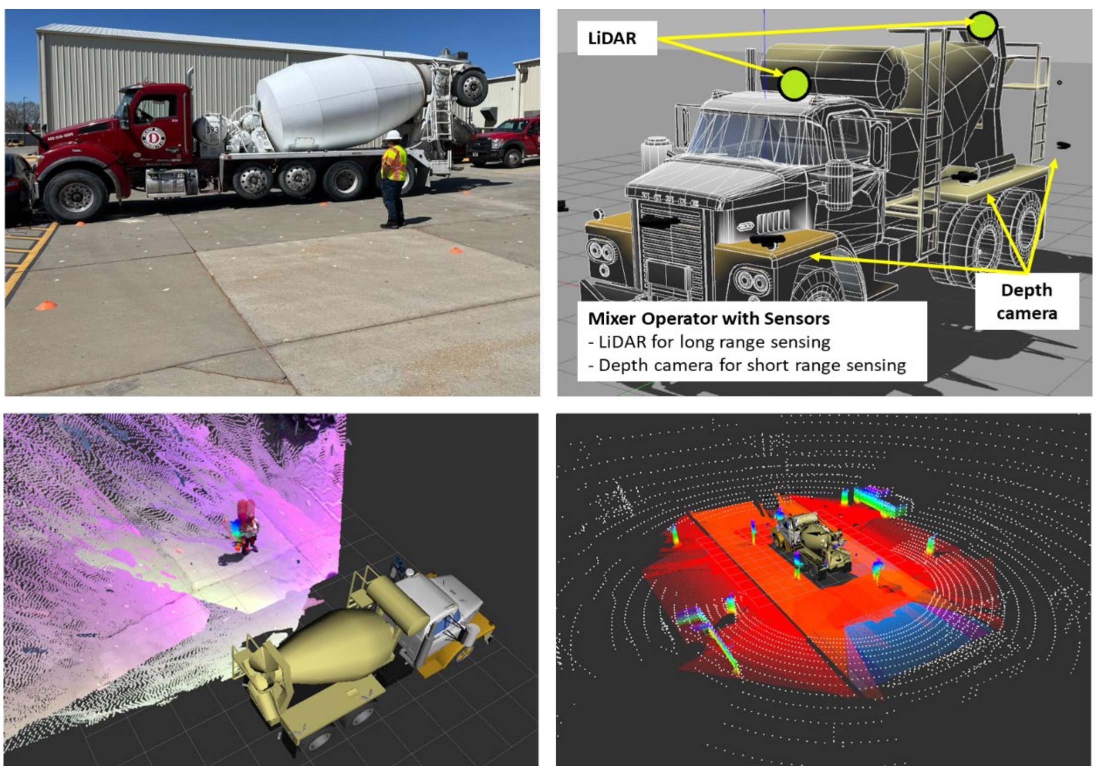
Introduction

Struck-by accidents in construction work zones

Construction and maintenance of highways and roads involve operations of heavy construction equipment (e.g., excavators, bulldozers, trucks), consistently exposing workers to hazards that could cause injuries and fatalities. Recent data covering 2013 to 2022 [1,2] reveal a total of 1,007 worker fatalities at road construction sites, averaging over 120 deaths per year. The primary causes of these fatalities were workers on foot being struck by vehicles (51.7%) and workers driving or riding in motor vehicles (26.3%); other causes included falls, slips, trips, electrocutions, and being caught in or between objects or equipment (21.9%). These figures highlight the persistent dangers faced by workers and the importance of innovative approaches to prevent safety hazards in road construction.

We believe a large portion of these work zone fatalities (including struck-by equipment, caught-in/between equipment, transportation-related incidents, and pedestrians struck by equipment) can be prevented if the equipment is able to automatically detect a wide variety of objects and alert operators of potentially unsafe situations in real-time. Such systems would rely on advanced sensing and perception technologies (e.g., cameras, LiDAR, and radar) to continuously monitor the environment around the equipment, identify hazards, and provide timely warnings to operators, allowing them to take actions before accidents occur (Figure 1).

Figure 1. (a) Mixer truck with sensors, (b) LiDAR and depth camera sensor placement, (c, d) 3D environment reconstruction and object detection



Tag-based approaches vs vision-based perception techniques

The use of sensor tags has been more extensively explored to monitor the proximity between workers and heavy equipment in construction zones. Several studies [3–6] attempted to detect proximity between workers and construction equipment using various types of sensor tags (e.g., BLE, magnetic, RFID, and UWB) attached to both equipment and workers. Approaches in tag-based proximity detection 1) attach sensor tags to heavy equipment and workers on foot, 2) convert the received signal strength (RSSI) between the tags to distances, and 3) alert workers and equipment operators when the estimated distances are within a threshold considered hazardous.

Despite some advantages, such as low cost and easy implementation, these tag-based approaches suffer from critical limitations that prohibit accurate and robust detection of unsafe situations in work zones. First, RSSI between tags and distance estimation are significantly impacted by objects around the equipment and workers. A wide variety of construction-specific conditions, such as stacking of materials, movements of workers, metallic equipment surfaces blocking sensor signals, and even weather conditions, cause Non-Line of Sight (NLOS) situations that affect the RSSI, leading to inaccurate distance estimation. Moreover, tag-based approaches cannot perceive the existence and locations of objects without tags (e.g., passenger vehicles, pedestrians, materials) that often cause unsafe situations. Relying solely on such “blinded” RSSI-based sensor tags prevents the generation of contextual information beyond rough distances.

On the other hand, by adapting vision-based perception techniques, situational awareness of heavy equipment operators can be greatly enhanced. Multiple sensors (e.g., RGB and RGBD cameras, LiDAR units, and radars) can be mounted on a piece of equipment to ensure 360-degree visibility. Real-time data from the sensors can reconstruct 3D scenes around the equipment to detect unsafe situations to communicate to the operator. By fusing data from high-resolution cameras and LiDAR units with millimeter-level accuracy, vision-based perception techniques can more accurately and robustly detect and track various types of objects with tags than tag-based proximity detection. These eventually would allow the detection of various unsafe situations beyond simple proximity detection.

Despite the promising potential of advanced vision-based perception technologies, their adaptation into heavy construction equipment has not been widely achieved or fully optimized. The literature review and in-depth interviews conducted by the PI with industry-leading companies revealed that state-of-the-art systems are limited in scope, primarily focusing on detecting the presence of human workers in relatively simple earthmoving environments. These technologies fall short in addressing the complexities of dynamic road construction sites, where unsafe situations can arise from factors such as interactions between equipment and workers, different operational contexts, and the surrounding environment.

For a sensing system to fully detect and respond to unsafe situations in these complex environments, it is crucial that the system can be customized. Each work zone and piece of equipment presents its own challenges. For example, custom sensor placement is required to account for blind spots and the varying shapes and sizes of equipment. Additionally, custom sensor programming is necessary to interpret sensor data based on the specific interactions happening in a particular work zone. Finally, checking rules must be developed to address the hazards that arise from different types of operations, interactions, and environmental conditions. Incorporation of these factors—sensor placement, programming, and safety rules—has not been thoroughly studied in the past or implemented before in a way that addresses the wide variability in road construction sites. Without this customization, current systems lack the flexibility to handle the dynamically changing risks that occur in different work zones.

Objectives

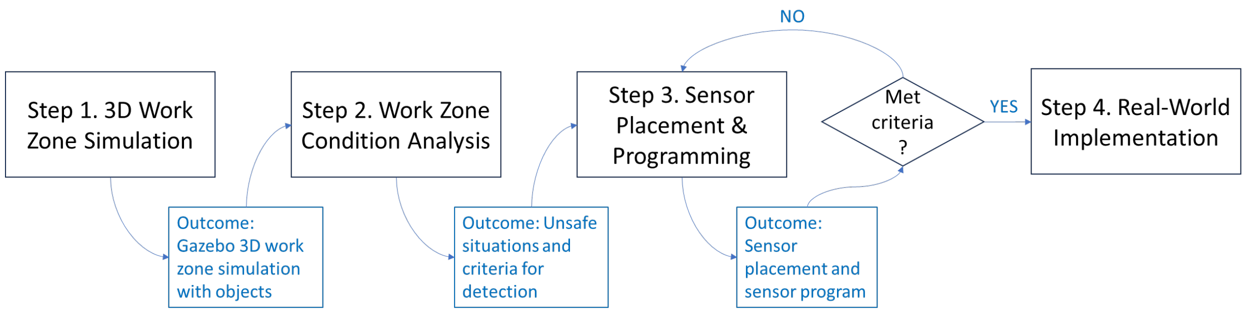
This project proposes a comprehensive framework designed to enhance safety by integrating sensor-based perception into heavy construction equipment. The framework consists of four essential steps: 1) creating a 3D simulation of the work zone and equipment to model interactions and environmental dynamics; 2) conducting a detailed work zone condition analysis and developing custom safety checking rules based on the specific environment and operations; 3) determining the optimal sensor placement on the vehicle and programming tailored to the conditions identified in the simulation; and 4) integrating the sensors into real-world equipment for practical application. By following this structured approach, contractors will be able to assess future work zones, identify unsafe situations, and develop and test sensor configurations within a 3D simulation environment before applying them to real-world scenarios.

The project developed a prototype solution based on the widely used Robot Operating System (ROS) [2] framework, leveraging the growing number of off-the-shelf sensors compatible with ROS. This approach simplifies software integration, reducing the need for significant modifications and focusing on hardware investment. The resulting prototype will be highly beneficial to contractors and heavy equipment manufacturers looking to retrofit their machines with enhanced operator awareness capabilities. By detecting workers on foot, nearby vehicles, and other equipment that is easy to miss due to blind spots, this system will provide significant safety improvements in complex and congested work zones.

Methodology

<u>Sensor integration framework description</u>

Figure 2. Framework for Vision-Based Sensor Integration



Note: Figure 2 illustrates the framework for vision-based sensor integration into heavy construction equipment, detailing the key stages in the process.

Step 1. Development of 3D work zone simulation (Figure 3)

The first step in the framework involves developing a 3D simulation of the work zone with Gazebo [7], a widely used 3D robotics simulator. This simulation allows for realistic testing of sensor placements, detection algorithms, and the movement of objects like workers and vehicles around the construction equipment. By using Gazebo, various sensor configurations can be tested in a controlled environment to ensure that sensors are correctly placed and that detection algorithms capture unsafe situations before transitioning to real-world applications.

Figure 3. 3D work zone modeling in Gazebo (left) and real-world scenario (right)

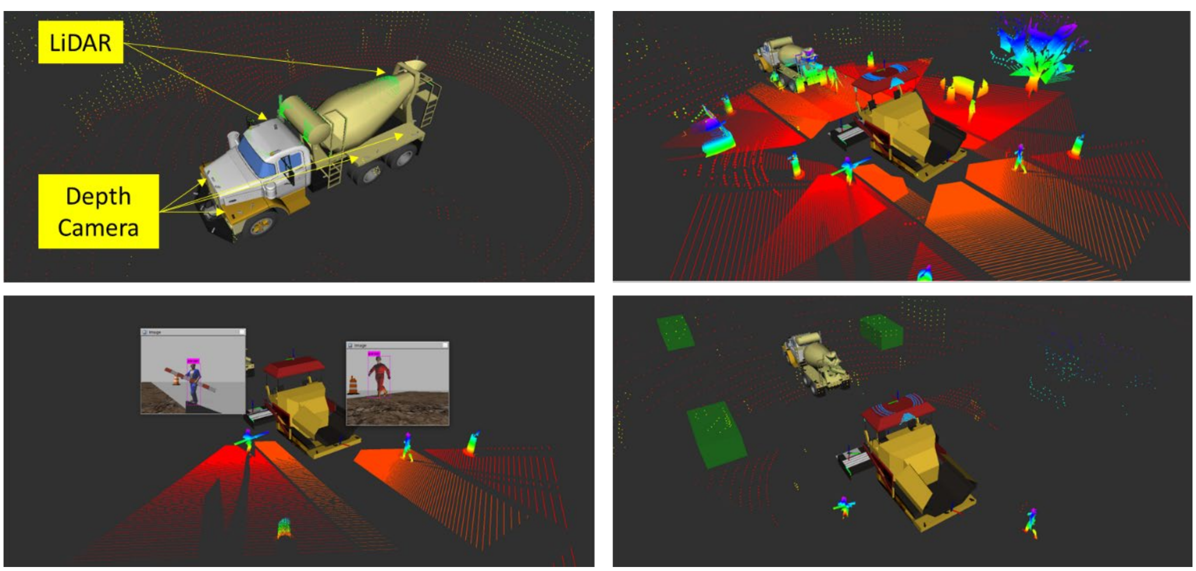
Step 2. Work zone condition analysis and criteria development

Work zone condition analysis primarily occurs within the 3D simulation environment. The simulation helps visualize the work zone layout, including dynamic interactions between equipment and workers. Additionally, Internal Traffic Control Plan (ITCP) diagrams and site photos serve as supplementary tools, providing insight into site-specific conditions that may not be fully captured by simulation alone. The results of the analysis inform the development of safety checking rules, which define what needs to be detected (e.g., workers, vehicles) and the distances or proximities that should trigger alerts. These rules are directly linked to criteria for evaluating the performance of sensor placement and sensor programs.

Step 3. Determination of sensor placement and programming (Figure 4):

Once the work zone conditions are understood, sensor placement begins within the Gazebo simulation environment. At this stage, users can adjust the sensor positions and orientations while visualizing the sensor data stream in RVIZ [8]. This initial process does not involve running detection programs; instead, it focuses on verifying whether the sensors provide full 360-degree visibility around the equipment, ensuring that all critical areas are covered. To do this, users manipulate elements within the simulation—such as moving workers, vehicles, and other objects around the equipment—to check that each object is observed by the sensors. This is a manual verification step where the goal is to confirm that objects are "seen" by the sensors, without yet activating detection algorithms. Once 360-degree visibility is confirmed, the next phase involves running the detection programs, which include a combination of object detection and location tracking algorithms. These algorithms are responsible for identifying objects, calculating their position relative to the equipment, and tracking their movements. Throughout this process, the sensor configuration—including their locations, orientations, and detection programs —is continuously refined. This iterative refinement ensures that the system meets predefined safety criteria. Adjustments are made to sensor parameters such as detection range, noise handling, and field of view. The goal is to optimize the sensor layout and detection performance until the system is robust enough to detect unsafe situations in real-world environments, aligning the simulation with actual conditions.

Figure 4. Sensor placement (top left), visibility test (top right), worker detection program test (bottom left), and vehicle detection program test (bottom right)



Step 4. Real-world implementation of sensor configuration:

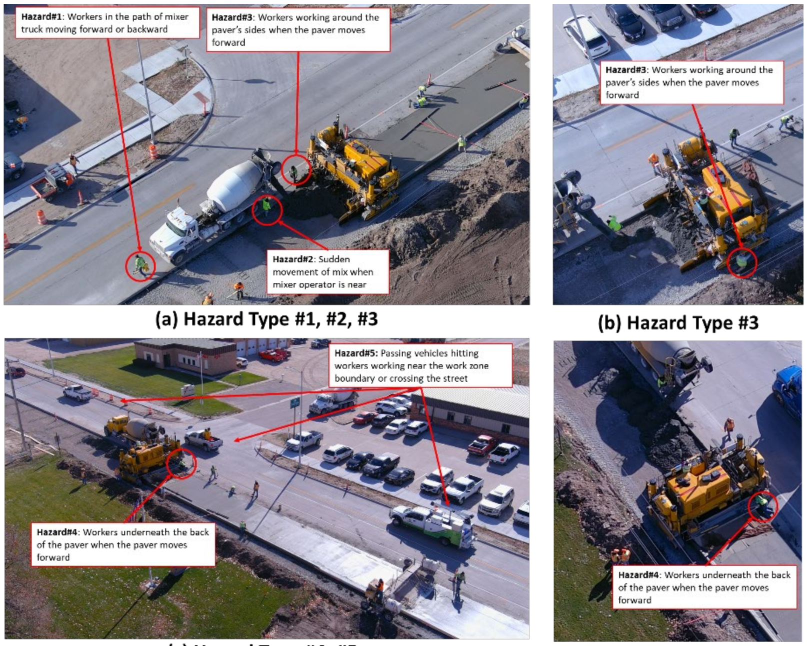
The final step involves implementing the final sensor configuration in real-world equipment. Sensors are physically mounted on the equipment according to the simulation, and the data stream is monitored through RVIZ. While real-time alerting for unsafe situations has not yet been implemented, the system lays the foundation for this capability, enabling future development that will notify operators of potential hazards detected by the sensors. Additionally, instead of storing the full raw data stream, only the processed results—such as object detection outcomes, object location tracking, and instances of unsafe situations—is saved locally on the computer attached to the sensors. In future implementations, if on-site internet connectivity is available, this data can be transmitted to remote locations for real-time monitoring of construction sites.

Case study

We collaborated with the Nebraska Department of Transportation (NDOT) and Lyman-Richey Corporation for a case study. With NDOT, we created a simulation of a representative work zone that contains various types of safety hazards. Open-ended discussions with NDOT helped us determine the specific phase and type of work zone to focus on. Additionally, we analyzed aerial videos from a completed NDOT project. Based on all of this input, the mixer truck, used in road paving, was selected as the target equipment due to its faster and more dynamic movements, which can pose greater safety risks than other, slower-moving equipment. As shown in Figure 5, we determined five potentially unsafe situations that the safety monitoring system needed to detect. The situations include “workers in the path of mixer truck moving forward or backward”, “sudden movement of mixer truck when mixer operator is near”, “workers working around the paver’s sides when the paver moves forward”, “workers underneath the back of the paver when the paver moves forward”, and “passing vehicles hitting workers working near the work zone boundary or crossing the street”. To ensure the system could detect the hazards, we established two primary criteria for sensor placement:

- Short-range depth cameras should be positioned to collect RGB images for image-based object detection and collect highly dense point clouds which provide geometric data of detected objects up to 6 meters. This ensures accurate detection and location tracking of workers and other objects at close distance. Point clouds, composed of numerous spatial data points, capture the 3D shapes of objects in the environment. See Figure 4 for point clouds in Gazebo simulation and Figure 7 top right for real point clouds.
- Long-range LiDAR sensors should be placed to collect point clouds of vehicles at distances up to 30 meters. This is essential for detecting vehicles approaching the work zone, providing operators with early warnings of potential dangers from incoming traffic.

Figure 5. Hazard analysis for typical paving construction environment



(a) Hazard Type #1, #2, #3

(b) Hazard Type #3

(c) Hazard Type #4, #5

(d) Hazard Type #4

We used two sensors for this project: Intel RealSense D455 depth sensors and Velodyne VLP-16 LiDAR. The Intel RealSense D455 was selected for worker detection for its ability to collect point cloud data in outdoor environments, providing a dense point cloud for objects within close range. The Velodyne VLP-16 was chosen for its ability to accurately capture point cloud data of vehicles approaching the work zone from over 30 meters. The properties of these sensors, including their field of view, point cloud density, and detection ranges, were carefully configured in the Gazebo simulation environment.

As shown in Figure 4, we moved virtual workers and vehicles within the simulation while adjusting the sensor locations and orientations. This was a manual process in this project, though future research may aim to automate this step. Each cycle of configuration adjustment took approximately 30 minutes, and we completed 10 rounds of adjustments. In each round, we tested the system's ability to achieve full 360-degree visibility, along with specific tests for worker and vehicle detection. Following these tests, we finalized the configuration and mounted the sensors on the mixer truck as shown in Figure 6, using the setup that passed all detection criteria. Detailed technical information about the sensor programming can be found in the referenced thesis [9].

We performed several experiments, including tests for location tracking accuracy and safety monitoring. In the worker location tracking experiment, the system achieved an average error of 27.1 cm (10.67 inches), with the framework reliably detecting workers who were within 5 meters (16.4 feet) of the equipment. For vehicle location tracking, the system detected approaching vehicles from 30 meters (98.43 feet) to 10 meters (32.8 feet) with an average error of 1.05 meters (3.44 feet), although it experienced difficulty in locating vehicles closer than 10 meters (32.8 feet) due to LiDAR limitations. A close-range vehicle detection test achieved an accuracy of 50.1 cm (19.72 inches) within 5 meters (16.4 feet) of the mixer truck. The safety monitoring experiment was particularly stringent, as it required immediate detection of worker entries and exits into predefined unsafe zones around the equipment. This test resulted in a sensitivity rate of 88.26%, meaning that the system could detect most entries and exits with less than 12% uncertainty. Full experimental plan and results can be found in the referenced thesis [9].

Figure 6. Placement of sensors in mixer truck

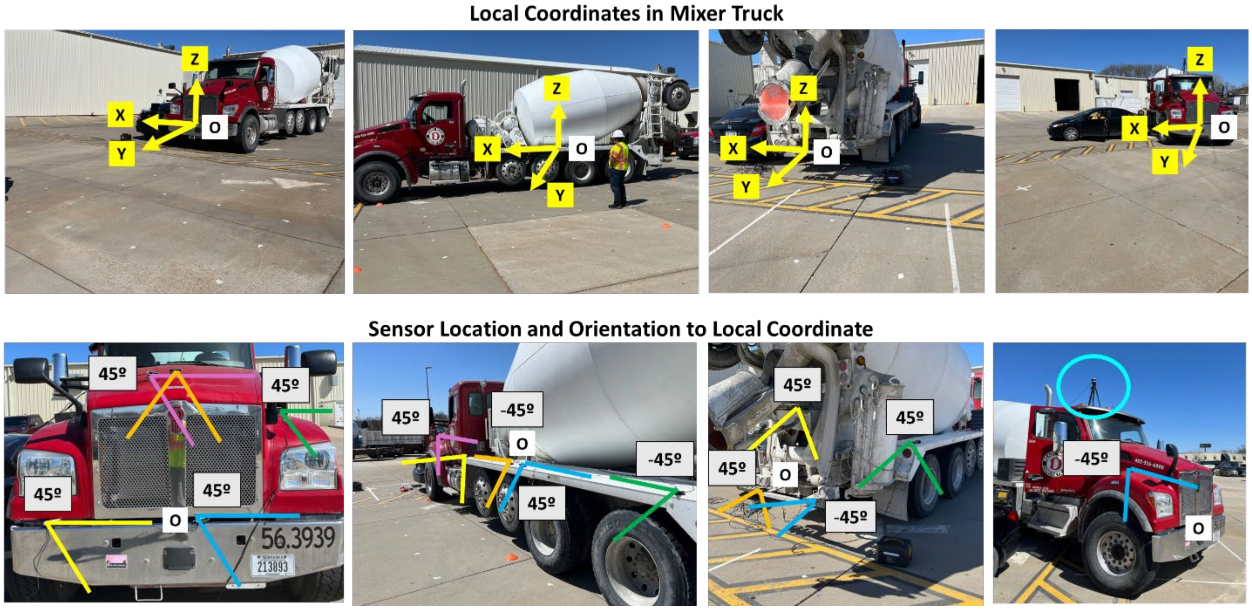
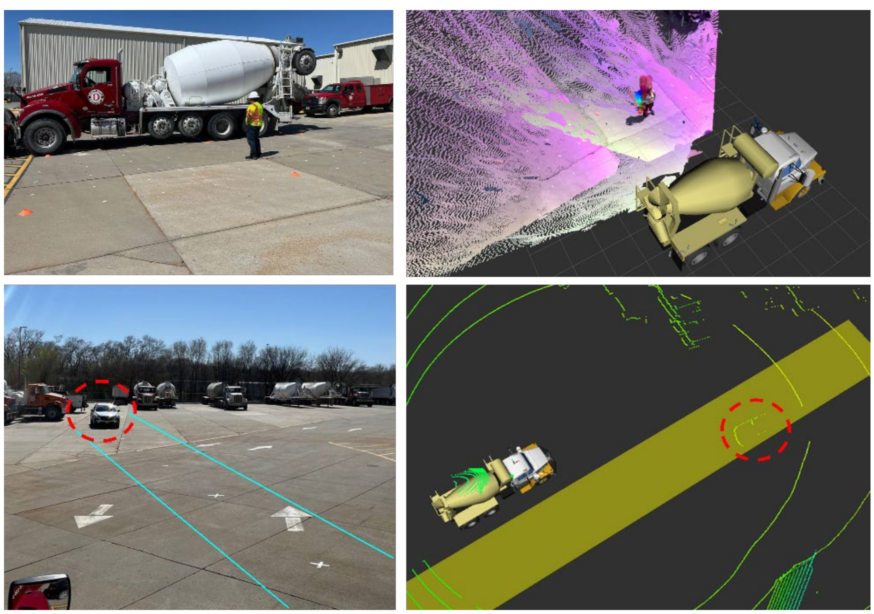


Figure 7. Worker detection and vehicle detection by the developed system (top left: worker next to mixer truck, top right: detected worker shown in 3D view, bottom left: vehicle approaching mixer truck, bottom right: detected vehicle shown in 3D view)



Accomplishments and results

- Development of a novel framework: The project successfully developed and tested a new framework for embedding sensor-based perception systems into heavy construction equipment.
- Creation of high-accuracy perception pipelines: Two sensor-based perception pipelines were developed to detect and track the locations of humans and vehicles with high accuracy.

These results significantly outperform traditional proximity detection methods that rely solely on signal strength measurements.

- Rapid integration capability: The use of simulation for sensor selection and placement not only enhances the detection of unsafe situations involving various objects and activities but also allows for rapid integration of sensors into new equipment types and different work zone environments, demonstrating flexibility and scalability of the approach.

Changes/problems that resulted in deviations from methods: N/A

Future funding plans

We are currently planning proposals to be submitted to the NCHRP Idea program and NIOSH R21 program to continue this research.

List of presentations and publications

- Development of a Rule-Based Safety Checking System for Autonomous Heavy Construction Equipment (2024). In Construction Research Congress 2024 [10].
- Development of a Rule-Based Monitoring System for Autonomous Heavy Equipment Safety (2024). MS Thesis, University of Nebraska-Lincoln [9].

Dissemination Plan

An open-source repository will be created after the final code reorganization to share the outcomes (ROS software code, sensor placement on selected equipment, system configuration, and user manual) of this project so that equipment manufacturers and developers can use the proposed framework to incorporate sensors into heavy construction equipment.

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