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**Innovations Deserving  
Exploratory Analysis Programs**

***Highway IDEA Program***

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*Development of a Sensing Methodology for Intelligent and  
Reliable Work-Zone Hazard Awareness*

Final Report for Highway IDEA Project 139

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**October 2011**

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**TRANSPORTATION RESEARCH BOARD**  
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*Development of a Sensing Methodology for Intelligent and Reliable Work-Zone Hazard Awareness*

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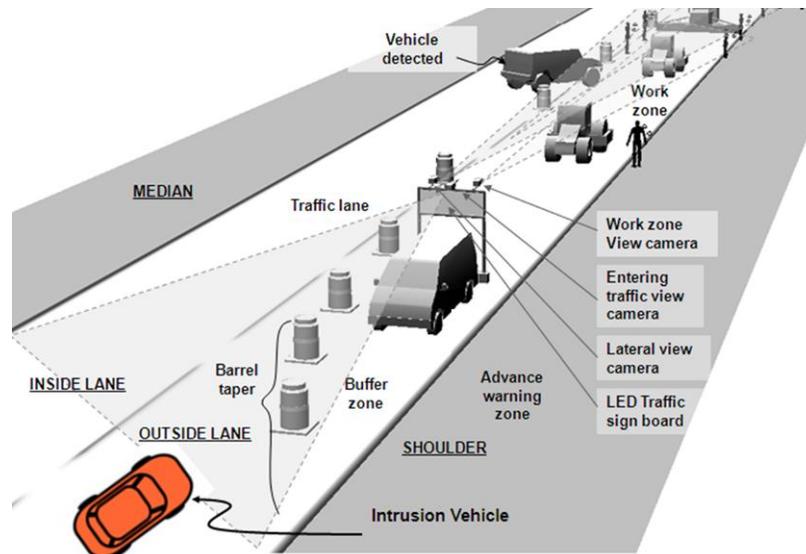
# TABLE OF CONTENT

ACKNOWLEDGEMENTS.....	i
TABLE OF CONTENT.....	ii
EXECUTIVE SUMMARY .....	iii
1. IDEA PRODUCT .....	1
2. CONCEPT AND INNOVATION.....	2
3. INVESTIGATION.....	4
3.1 WORK ZONE HAZARD AWARENESS SYSTEMS.....	4
3.1.1 <i>Review of Existing Work Zone Hazard Awareness Systems</i> .....	4
3.1.2 <i>The Proposed Vision-based Work Zone Hazard Awareness Methodology</i> .....	5
3.2 INTRUDING VEHICLE AWARENESS ALGORITHM.....	6
3.2.1 <i>Review of Vision-based Vehicle Detection Algorithms</i> .....	6
3.2.2 <i>Vehicle Detection</i> .....	7
3.2.3 <i>Vehicle Tracking</i> .....	10
3.2.4 <i>Surrogate Extraction</i> .....	11
3.2.5 <i>Decision Support</i> .....	11
3.2.6 <i>Experimental Results</i> .....	12
3.2.7 <i>Summary</i> .....	15
3.3 MISSING TRAFFIC CONTROL DEVICE AWARENESS ALGORITHM.....	15
3.3.1 <i>Review of Missing Traffic Control Device Awareness Algorithms</i> .....	15
3.3.2 <i>Traffic Control Device Detection</i> .....	16
3.3.3 <i>Traffic Control Device Tracking</i> .....	17
3.3.4 <i>Surrogate Extraction</i> .....	18
3.3.5 <i>Decision Support</i> .....	18
3.3.6 <i>Experimental Results</i> .....	19
3.3.7 <i>Summary</i> .....	21
3.4 POTENTIAL APPLICATIONS ON DRIVER BEHAVIOR STUDY.....	21
3.4.1 <i>Proposed Method</i> .....	21
3.4.2 <i>Preliminary Results</i> .....	22
3.4.3 <i>Summary</i> .....	23
4. CONCLUSIONS AND RECOMMENDATIONS.....	25
5. PLANS FOR IMPLEMENTATION.....	27
REFERENCES .....	28

## EXECUTIVE SUMMARY

Work zones create significant safety concerns that have recently intensified because of the increasing number of roadway widening, rehabilitation, and reconstruction projects. There is an urgent need to develop technologies to improve work zone safety. Although some technologies, such as the laser switch, can detect intruding vehicles, they are not reliable enough to function practically. In this regard, state departments of transportation (DOTs) recognize that system intelligence and reliability are the keys to making a hazard awareness system work effectively.

This project proposes a vision-based work zone hazard awareness methodology to intelligently and reliably detect intruding vehicles and missing control devices in work zones so early warnings can be activated to avoid safety hazards for workers and drivers. Two vision-based algorithms that detect intruding vehicles and missing traffic control devices have been developed in the proposed methodology. These two algorithms will serve as the core for developing an integrated, intelligent work zone hazard awareness and warning system, as shown in Figure 1. To the best of our knowledge, there is no publication on developing vision-based work zone intruding vehicle and missing traffic control device detection algorithms. In this study, reliable intruding vehicle and missing traffic control device awareness algorithms have been developed to address the unique technical challenges, including vehicle occlusions, changing lighting conditions, etc., when applying vision technology in work zones.



**Figure 1 An Integrated, Intelligent Work Zone Hazard Awareness and Warning System**

The proposed algorithms for detecting intruding vehicles and missing traffic control devices have been tested using a simulated work zone on Georgia Tech's Savannah campus. The tests have demonstrated that intruding vehicles and missing cones can be reliably detected, and the developed work zone hazard awareness algorithms are promising. The accuracy and reliability of these vision-based algorithms can be further refined with

additional testing. In addition, a 30-ft mobile work zone traffic data collection and monitoring tower, equipped with multiple cameras, has also been developed and successfully implemented in this project to collect actual traffic data in a work zone on I-95 near Savannah, Georgia. Different drivers' merge behaviors from different roadway geometries, such as curved or straight roads, have also been studied.

With the promising preliminary outcomes, the principal investigator is initiating a follow-up research project, sponsored by the Georgia Transportation Institute/ University Transportation Center (GTI/UTC) and the Georgia Department of Transportation (GDOT), to apply the vision-based algorithms to the development of a real-time driver behavior feedback system. The system will gradually improve drivers' unsafe behaviors in work zones and provide an effective means to quantitatively evaluate the performance of the proposed system.

# 1. IDEA PRODUCT

The products of this IDEA concept exploration research project include a vision-based work zone hazard awareness methodology, two algorithms, and a 30-ft mobile traffic data collection and monitoring tower. The two algorithms, which employ vision technology, were developed to intelligently and reliably detect intruding vehicles and missing control devices (e.g. cones/drums) in work zones so that early warnings can be activated to warn workers and drivers of hazards. The 30-ft mobile tower, equipped with multi-view cameras that can comprehensively cover a work zone, as shown in Figure 2, was used to monitor and record actual traffic data in work zones on I-95 near Savannah, Georgia, to support quantitative driver behavior studies and vehicle trajectory analyses. The proposed methodology, along with the developed algorithms, will serve as the essential foundation for developing an integrated, intelligent vision-based work zone hazard awareness and warning system. In the future, an integrated work zone hazard awareness and warning system can be developed by incorporating other sensing technologies, including wireless technology, vehicle infrastructure integration (VII) communication, vibrating wristbands, headphones, sirens, smart phones, etc., to provide timely warnings to workers, drivers, authorized managers, and emergency response units. Along with the computed driver trajectories, the actual traffic data in work zones can be used to quantitatively study work zone driver behaviors, which, previously, has been very difficult to do. This will provide an effective means for engineers to quantitatively evaluate the performance of different work zone traffic control devices and traffic control configurations, etc., in terms of their impact on driver behaviors, traffic safety, and mobility in work zones.



(a) Multi-view Cameras



(b) Tests Conducted on I-95 Work Zone

**Figure 2 A Prototype 30-ft Mobile Work Zone Traffic Data Collection and Monitoring Tower**

## 2. CONCEPT AND INNOVATION

Highway work zone safety is very important. Although many work zone hazard awareness systems have been developed and tested, most of them lack system intelligences and reliability to a) provide early warning to workers and drivers and b) differentiate a flying object or a worker from an intruding vehicle, which causes frequent false alarms. Moreover, setting up of these systems, such as the installation of impact-detection devices on cones or adjusting the alignment of the laser switch, etc., is tedious and time-consuming, and it requires additional efforts from workers (Burkett and Her 2009). This IDEA exploration research project proposes a vision-based work zone hazard awareness methodology that can easily, efficiently, intelligently, and reliably detect work zone hazards, provide early warning to improve highway work zone safety, and minimize interference with existing work zone activities. It uses vision technology, which has the following strengths: a) it can efficiently cover large areas and accurately identify potential hazards; b) it is low cost; and c) it is relatively easy to set up and transport. The innovations of this research, including a) the developments of the two vision-based algorithms that can intelligently and reliably identify intruding vehicles and missing traffic control devices and b) the development of a 30-ft mobile work zone traffic data collection and monitoring tower that can be applied to help understand the impact of different traffic control strategies on driver behaviors, are discussed below.

Many vehicle detection and tracking algorithms have been developed over the past decades; however, most of them have limitations dealing with vehicle occlusions in images. Due to limited camera angles and frequent congestions in work zones, the chance of vehicle occlusions increases significantly. Although there have been several previous studies on vehicle occlusion detection, reasoning, and reconstruction (Alcantarilla et al. 2008; Pang et al. 2007), it is not feasible to employ these algorithms in work zones due to their complex nature. To address these technical challenges, an innovative, tire-based vehicle detection algorithm that consists of three steps including a) the adaptive background construction using recursive median method, b) the vehicle tire detection using a proposed tire probability based on unique characteristics of a tire feature, and c) the tire association and detection validation process, has been developed in this research. The tire-based vehicle detection algorithm and other intruding vehicle hazard awareness processes (e.g., vehicle tracking, decision making, etc.) together constitute an innovative vision-based algorithm, i.e., the intruding vehicle awareness algorithm in this research, to intelligently and reliably detect potential intruding vehicle hazards in work zones.

Traffic control devices, such as traffic cones and barrels, play a critical role in guiding traffic and delineating work zones. These devices may be frequently removed or damaged by swerving/swaying trucks or extreme weather conditions, such as strong winds or storms. Missing or displaced traffic control devices in the transition area or the work zone activity area can critically endanger workers and drivers. These missing devices may lead to drivers' misunderstanding of the work zone delineation and result in dangerous situations. Currently, missing work zone traffic control devices are usually detected by flaggers, project inspectors, contractors, or workers in the work zone; unfortunately, these workers cannot be on site twenty-four hours a day. There is a need to develop a system that can monitor the work zone taper twenty-four hours a day, detect displaced or missing traffic control devices, and inform

responsible authorities of the need to remedy the situation. An innovative algorithm, i.e., the missing traffic control device awareness algorithm, has been developed to reliably and effectively detect missing traffic control devices.

Finally, it is noteworthy that current safety studies have focused on corrective actions that have had relied on police crash reports (Ullman et al. 2011); these studies cannot reflect the true causes of crashes or driver behaviors; they lack the means of recording and extracting vehicle information and drivers' behaviors prior to the crashes. Therefore, in addition to the aforementioned hazard awareness algorithms, a 30-ft mobile work zone traffic data collection and monitoring tower, which is equipped with multi-view cameras that cover different work zone areas (e.g., the advance warning area, the transition area, the work zone activity area, etc.), has also been developed in this project to collect and monitor traffic data in work zones. The mobile tower and vehicle trajectories derived from the intruding vehicle awareness algorithm can be applied to study driver behaviors in work zones and provide an effective means to quantitatively evaluate the performance of different traffic control strategies in relationship to work zone safety and mobility. This can further lead to the development of state DOTs' design of work zone configuration guidelines under different roadway geometries, traffic conditions, weather conditions, etc.

### **3. INVESTIGATION**

This chapter is organized into five sections. The first section reviews existing work zone hazard awareness systems to identify the research need; the second section presents the proposed vision-based work zone hazard awareness methodology; the third section introduces the developed intruding vehicle awareness algorithm; the fourth section introduces the developed missing traffic control device awareness algorithm; and, the fifth section discusses the potential use of the developed 30-ft mobile work zone traffic data collection and monitoring tower to gather information for studying driver behaviors.

#### **3.1 WORK ZONE HAZARD AWARENESS SYSTEMS**

##### **3.1.1 Review of Existing Work Zone Hazard Awareness Systems**

Work zone crashes lead to about 600 fatalities and 50,000 injuries every year (NHTSA 2010). Improving work zone safety has been a pressing concern for federal and state transportation agencies, and this concern has been intensified by the increasing number of roadway maintenance and rehabilitation projects. Many work zone hazard awareness systems have been developed in recent years. These systems can be divided into three major categories: mechanical systems, electronic systems, and dedicated observers (Bryden and Mace 2002). Mechanical systems use mechanisms, such as impact-activated or pressure-activated systems, which are triggered by physical contacts or impacts of intruding vehicles. Examples of mechanical systems are pneumatic tubes (Carlson et al. 2000; Trout and Ullman 1996), which use the change of air pressure to detect intruding vehicles, and the SonoBlaster (Transpo 2010), which issues an alarm when the cone equipped with the impact-detection sensor is physically struck by the intruding vehicle. Electronic systems apply sensing technologies, such as laser switch systems, which require the alignment of transmitters and receivers to detect intruding objects. If a receiver fails to receive signals from a transmitter, the system activates an alarm. Examples of electronic systems include infrared beam systems and ultrasonic beam systems studied in the SHRP research (Epps and Ardila-Coulson 1997), the microwave beam system developed by the Traffic Management System Crop (Burkett and Her 2009; Kozdon 1982), and infrared systems (Hagan 2004; Sullivan 2005). Other practices employ dedicated observers, such as workers or flaggers, to spot intrusions and trigger alarms (Antonucci et al. 2005; Bryden and Mace 2002).

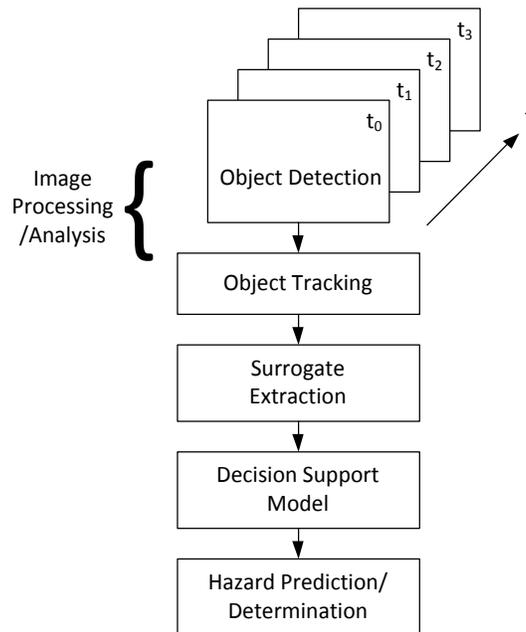
In the systems mentioned above, the following issues remain unresolved. First, the systems do not have the intelligence to differentiate harmless objects, such as a flying plastic bag, from intruding vehicles, resulting in frequent false alarms that seriously degrade the reliability of the developed system. Second, electronic systems, such as the laser switch, heavily rely on the alignment of a transmitter and a receiver that can easily be blocked or moved by trucks passing by, and lead to malfunctioning systems. Third, these systems cannot detect the speeds and trajectories of vehicles, so they cannot warn drivers or workers before vehicles intrude into the work zone.

In summary, lack of system intelligence and reliability are two key factors that hinder the successful implementation of existing systems. Therefore, there is a need to develop an intelligent and reliable work zone hazard awareness system. With the advance of information and sensing technologies, high-resolution and low-cost cameras have

become available. Great system intelligence and reliability can now, potentially, be achieved by employing image sensing technologies. First, besides the low cost of cameras, the vision-vision system covers a large view of the work zone and can detect/predict intruding vehicles before they disrupt the work zone taper. Second, through image processing, a vision-based system is capable of differentiating a flying bag from an intruding vehicle. Computer vision techniques have been extensively used to support traffic information collection and to improve intersection safety (Atev et al. 2006; Kim et al. 2007; Saunier and Sayed 2006; Veeraraghavan et al. 2003). They have also been used to detect and track vehicles and recognize objects, such as traffic signs, based on their features, including colors, shapes, and textures (Tsai and Wu 2002; Tsai et al. 2005; Wu and Tsai 2005; Wu and Tsai 2006; Wu and Tsai 2006). Therefore, because of the reliability and intelligence of computer vision technologies that have been successfully applied in various field applications, a vision-based work zone hazard awareness methodology is proposed in this study.

### 3.1.2 The Proposed Vision-based Work Zone Hazard Awareness Methodology

In this section, a vision-based work zone hazard awareness methodology is proposed. As shown in Figure 3, the proposed methodology consists of four major components, including object detection, object tracking, surrogate extraction, decision support model, and hazard prediction/determination.



**Figure 3 A Vision-based Work Zone Hazard Awareness Methodology**

In general, there are two types of work zone hazards: a) Case 1: hazards along the work zone tapers (e.g., boundary), e.g., intruding vehicles, and missing traffic control device; and b) Case 2: hazards inside work zones, e.g., hazardous operations involving machinery and workers. This study currently focuses only on the Case 1 work zone hazards. To intelligently and reliably detect work zone hazards, the proposed vision-based methodology includes object detection and tracking capability to improve the reliability of determining potential hazards and appropriate actions

to take. The object tracking function will be capable of intelligently predicting the occurrence of a hazard based on an intruding vehicle's trajectory. The object tracking function can also be used to eliminate abnormal or incorrect detections and improve system reliability. For example, temporary occlusions may lead to the discontinuous trajectory of an approaching vehicle, which may lead to an incorrectly computed speed and an unreliable detection of the intruding vehicle; however, with the tracking function, discontinuous trajectories can be associated to reliably track the vehicle in the image sequence.

In addition, rich surrogates, including the distance to a work zone taper, the speed of a vehicle, the position of a vehicle, the surrounding traffic conditions (which allow the vehicle to merge or not), the presence of traffic control devices, the gaps between vehicles, the traffic flow, the traffic density, etc., can be obtained through a vision-based system. These surrogates can then be used to develop a decision-support model (deterministic or probabilistic) to more reliably determine/predict the occurrence of potential hazards.

### **3.2 INTRUDING VEHICLE AWARENESS ALGORITHM**

This section first reviews relevant vision-based vehicle detection algorithms, followed by the description of the developed work zone intruding vehicle awareness algorithm. The main steps of the algorithm, including vehicle detection, vehicle tracking, surrogate extraction, intrusion decision support, and experimental results, are presented below.

#### **3.2.1 Review of Vision-based Vehicle Detection Algorithms**

The core of vision-based vehicle detection algorithms is to distinguish moving objects (i.e. vehicles) from static objects (e.g., road, bridge, guardrails, vegetation, etc.). This is typically accomplished by differentiating foreground pixels from background pixels in the image. Three typical categories of vehicle detection are frame differencing, optical flow, and background subtraction. First, the frame differencing is a simple method that applies thresholding to the difference map, which is obtained by subtracting the previous frame from the current frame (He and Yung 2007; Yong-Kul and Dong-Young 2007). However, this method may be sensitive to the thresholds used, and "ghost objects" may be observed if the current frame does not have the moving object in the previous frame. Second, the optical flow estimates the motion vector field between two frames. One of the advantages of this method is that it also works with a moving camera. However, it is computationally expensive, since it is an iterative method that minimizes the energy or cost. Third, the background subtraction divides an image into either foreground or background. This method has been intensively applied in real-time transportation applications with fixed cameras (Ambardekar 2007; Cheung and Kamath 2004; Grammatikopoulos et al. 2005; Kanhere et al. 2010; Li et al. 2010; Mohaghegh and Rezaie 2005; Oh et al. 2010).

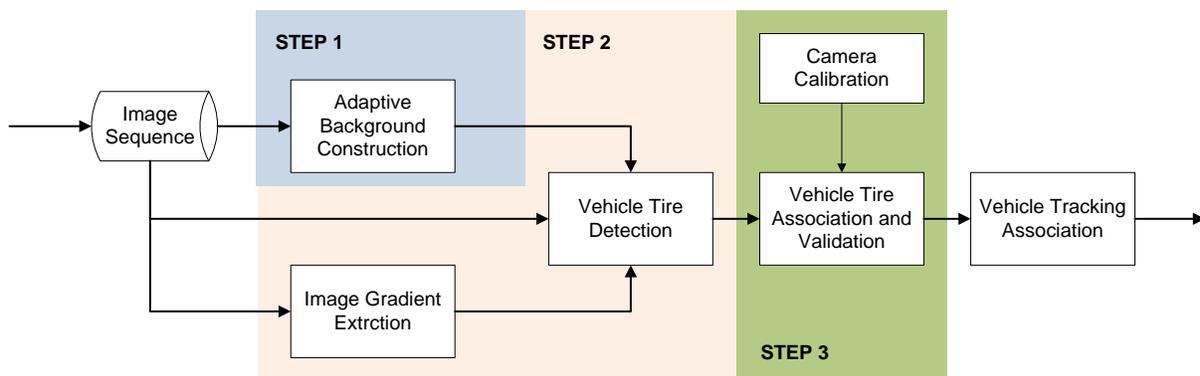
Once the foreground pixels are detected in the images, different methods are then applied to recognize the moving objects. For vehicle detection, four major methods have been used: region-based, model-based, feature-based, and contour-based. 1) The region-based method is typically based on the analysis of the foreground mask from the motion detection. Foreground blobs are grouped or separated by using algorithms, such as connected component

analysis. This method may get results, but the detection and grouping of blobs can be heavily affected by the occlusion of vehicles. 2) The model-based method uses a model-matching approach in which the detected blobs are compared with several pre-established 3D models to define what kind of vehicles they are (Pang et al. 2004; Pang et al. 2007). However, this method is time consuming and impractical, since there are too many types of vehicles and other objects on the road. 3) The feature-based method takes advantage of the common features of vehicles, such as window corners, bumper edges, head/rear lights, and shadows (Beymer et al. 1997; Kanhere and Birchfield 2008; Kanhere et al. 2005; Saunier and Sayed 2006). This method is limited in its range of detection, since these features may not be obvious when vehicles are far away. 4) The contour-based method is based on the active contour method that tracks the boundary of vehicle body (Paragios and Deriche 2000). The advantage of this method is that its representation is simple. However, the initialization of the foreground mask is crucial to the success of this method, and vehicle occlusion is still a challenge.

Vision-based vehicle detection remains a challenge especially for occluded vehicles. Moreover, in work zones, due to traffic congestion and limited camera angle, the chance of vehicle occlusions increases tremendously. These challenges may seriously affect the detection and tracking of vehicles in work zones using vision-based algorithms. Although there have been several previous studies on occlusion detection, reasoning, and reconstruction (Alcantarilla et al. 2008), they are not feasible for the work zone scenes due to the complexity and intensive computation of the algorithms. Therefore, there is a need to develop algorithms to address the unique challenges, such as detecting occluded vehicles, to provide a feasible means for employing vision technology in work zones.

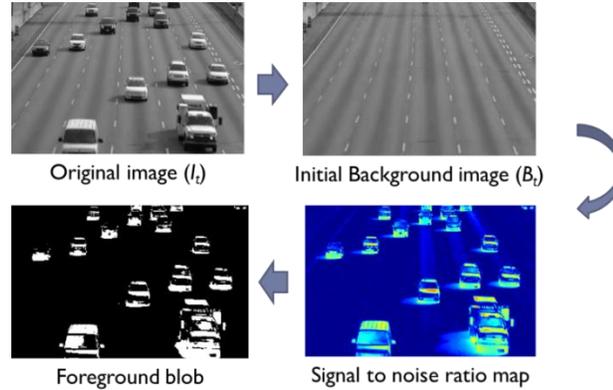
### 3.2.2 Vehicle Detection

The proposed vehicle detection method, as shown in Figure 4, consists of three major steps: the background construction, vehicle tire detection, and tire association and validation. The background construction step determines the background and foreground regions in an image based on the signal-to-noise ratio (SNR). The vehicle tire detection step detects vehicle tires in images. The tire association and validation step associates and validates detected tires and generates final detected vehicle blobs.



**Figure 4 Flowchart of the Proposed Vehicle Detection Method**

The procedure for the background construction step (Step 1) is presented in Figure 5. An initial background map ( $B_t$ ) is first generated at time  $t$  for each of the image pixel based on the average intensity of each pixel in the previous frames.



**Figure 5 The Background Construction Procedure**

For each incoming image frame (original image,  $I_t$ ), the SNR map is computed, using Equation 1, to represent the difference of intensity between a pixel in the current frame ( $I_t(x,y)$ ) and the corresponding pixel in the background map ( $B_t(x,y)$ ) (McFarlane and Schofield 1995). Here,  $\sigma(x,y)$  denotes the standard deviation of pixel intensities of pixel  $(x,y)$  in previous frames when constructing the background. A larger SNR represents a higher probability of a pixel being the foreground pixel.

$$SNR(x, y) = \frac{|I_t(x, y) - B_t(x, y)|}{\sigma(x, y)} \quad (1)$$

The SNR map is used to determine the foreground object (i.e. the vehicle) and background (i.e. the road) using a hysteresis thresholding  $k$ , as shown in following equation. Typically  $k = 3$  because 99.8% of the Gaussian distribution is between  $-3\sigma$  and  $+3\sigma$ .  $D_t$  is the indicator of the foreground vehicle.

$$D_t = \begin{cases} 1, & \text{if } |I_t - B_t| > k \cdot \sigma \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Once the background is adaptively constructed, the foreground blob in Figure 5 is considered as a vehicle candidate that will need further vehicle tire detection, association, and validation. This recursive approach is capable of adapting to changing lighting conditions caused by the change of sunshine, shadows, etc., which is frequently seen in work zone scenes.

The vehicle tire detection step (Step 2 in Figure 4) is performed based on the foreground map constructed in the previous step. Vehicle tires have the following unique features that can help improve the reliability of vehicle detection results:

- Vehicle tires have relatively low intensity and have a direct contact point with the road;
- A vehicle body, i.e., the foreground or high SNR blob, is directly on top of the tires in the image; and
- The road, i.e., the background or low SNR blob, is directly at the bottom of the tires in the image.

Based on these three distinguishing features, a probability,  $P_{tire}$ , is introduced to define the likelihood of a pixel being a tire pixel. This probability can be computed using three independent probabilities associated with the aforementioned three unique features.  $P_1$ ,  $P_2$  and  $P_3$  represent the probabilities of a pixel in the gradient map of the image on a horizontal edge, a pixel in the SNR map has the pixels on the top of the horizontal edge with high SNR, and a pixel in the SNR map has the pixels on the bottom of the horizontal edge with low SNR, respectively.  $P_{tire}$  is the product of the three probabilities, representing the probability of the current pixel in accordance with the tire characteristics identified. Pseudo-Code 1 shows the detailed process of determining each individual probability. To determine whether a pixel is a tire pixel based on the tire probability, a 70% threshold is used in this study on a trial-and-error basis.

### Pseudo-Code 1 Determination of the probability of tire pixel

---

```

1: for each column do
2: //Up-down scanning
3:  $\Sigma_{SNR} = 0$ 
4: for each pixel  $(x, y)$  do
5:  $\Sigma_{SNR}(x, y) = \Sigma_{SNR}(x-I, y) + SNR(x, y)$ 
6: if  $(x, y)$  detected as foreground then
7:  $P_1(x) = P(I(x, y)) \cdot P(\text{Gradient}_h(x, y))$ 
8:  $P_2(x) = P((\Sigma_{SNR}(x, y) - \Sigma_{SNR}(x-h_1+I))/h_1)$ 
9: end if
10: end for

11: //Down-up scanning
12:  $\Sigma_{SNR} = 0$ 
13: for each pixel  $(x, y)$  do
14:  $\Sigma_{SNR}(x, y) = \Sigma_{SNR}(x+I, y) + SNR(x, y)$ 
15: if  $(x, y)$  detected as foreground then
16:  $P_3(x) = P((\Sigma_{SNR}(x, y) - \Sigma_{SNR}(x+h_2+I))/h_2)$ 
17:  $P_{tire}(x) = P_1 \cdot P_2 \cdot P_3$ 
18: else
19:  $P_{tire}(x) = P_1 \cdot P_2 \cdot P_3$ 
20: end if
21: end for
22: end for
23: Result = Hysteresis ( $P_{tire}$ )

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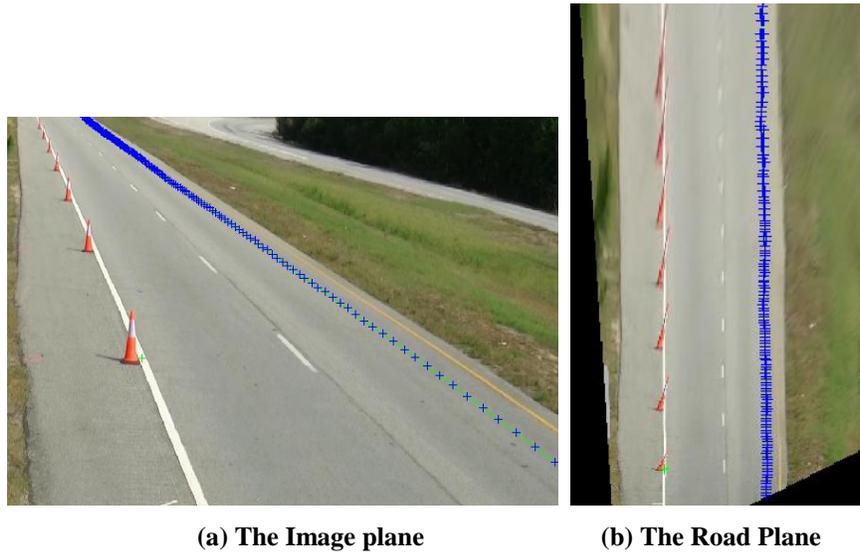
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Once vehicle tires in an image are detected, the detection association and validation step (Step 3 in Figure 4) is then conducted. The objective of detection association is to associate the individually detected tire with its corresponding vehicle. A 10-foot longitudinal offset and an 8-foot lateral offset are used to associate two detected tires as they should be treated as one vehicle. The remaining unassociated detected tires are validated using their vertical heights; any detection higher than 3 feet from the ground (i.e., side mirrors) is determined to be false. The rest of the unassociated detections are then validated using vertical gradients to determine the presence of vehicle occlusion; if a vertical gradient (the side of a vehicle) is found in front of a detection, the detected tire is then treated as part of a

detected occluded vehicle and a default vehicle width is assigned to the detection. Finally, the remaining unassociated detections are considered as isolated tire detections (i.e. motorcycles).

### 3.2.3 Vehicle Tracking

Once the vehicle detection steps are finished, vehicle tracking is performed to associate detections in the image sequence. As pointed out in the literature, it is more reliable to conduct vehicle tracking using the road plane coordinates instead of image coordinates (Palaio et al. 2009), for the speed of a vehicle is directly related to real-world values in the road plane coordinates. In other words, vehicle motion is more predictable in the road plane coordinates. As shown in Figure 6, the blue crosses represent a vehicle's positions along the trajectory. The actual moving distance between any two consecutive blue crosses along the trajectory is the same. However, as shown in Figure 6a, on the image plane, the closer the vehicle, the larger the pixel distance between two consecutive blue crosses, which indicates that it is difficult to predict a vehicle's positions using the image plane coordinates. Vehicle trajectory on the road plane, as shown in Figure 6b, on the contrary, shows constant distance (in pixels) between any two consecutive blue crosses, which reveals a simple and direct relationship with the actual distance between two consecutive blue crosses and can be used to better predict vehicle position. Therefore, in this study, we first transform the image coordinates to the road plane coordinates by applying the homographic matrix that projects the image plane (Figure 6a) on to the road plane (Figure 6b) and use the road plane coordinates to perform vehicle tracking and surrogate extraction.

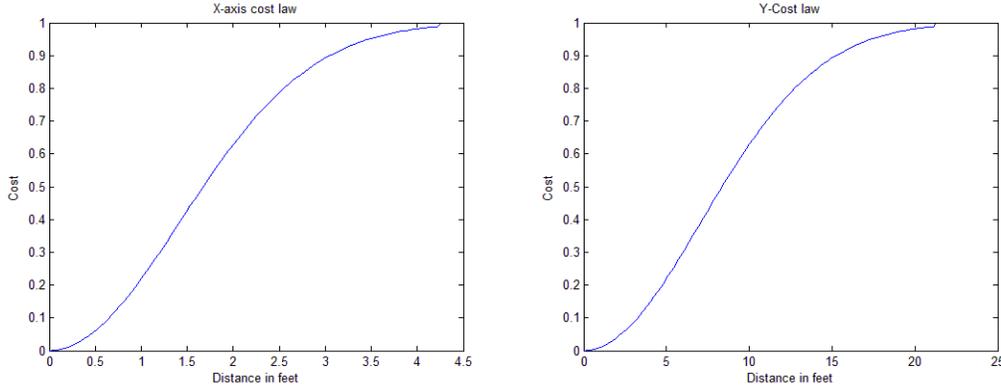


**Figure 6 Image Plane and Road Plane Vehicle Trajectory**

As mentioned previously, vehicle tracking in this study is accomplished by associating detections with the minimum cost in two consecutive images. In Equation 3, the vehicle position at time  $t$  is first estimated using the position ( $X_{t-1}$ ) on the road plane and the speed ( $V_{t-1}$ ) in the previous frame. The cost vector ( $cost_x, cost_y$ ) is then computed using the difference vector ( $\Delta x, \Delta y$ ) between the prediction and the actual detection, along with their corresponding costs using the cost laws shown in Figure 7. The cost laws are upside-down centered Gaussian laws adjusted by a parameter setting the maximum allowed speed error. In other words, vehicle detection cannot be associated with a

track if the distance travelled between two frames is related to change in speed that is too large. The cost laws also reflect the finite acceleration of the car. Two different cost laws for the  $x$  and the  $y$  axis have been designed in order to reflect the lateral inertia of a car going straight on the highway as well as the smaller probability of lane change. Finally, for each detection in the current frame, a track is associated with the corresponding detection that has the smallest cost vector in the previous frame. Once the tracking association is done, the speed is estimated using the new detection localization in order to be able to predict the position of vehicle in the next frame.

$$X_t^p = X_{t-1} + V_{t-1} \quad (3)$$



**Figure 7 Distance Cost Laws**

### 3.2.4 Surrogate Extraction

After the vehicle detection and tracking processes, surrogates, such as distance, speed, etc., are extracted. The vehicle distance can be extracted by computing the distance between the vehicle position ( $X_t$ ) and a point/line in the image; vehicle speed, on the other hand, is computed using the following equation:

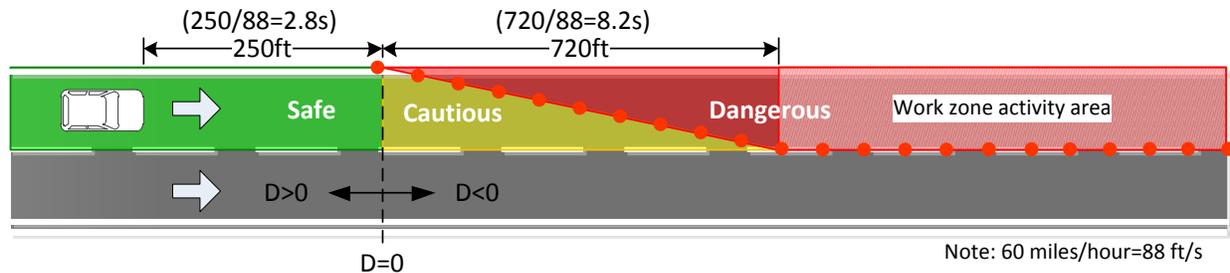
$$V_t = \frac{1}{k} \sum_{n=t-k}^t \frac{\|X_n - X_{n-d}\|}{d \cdot \Delta t} \quad (4)$$

In this equation, the speed of a vehicle at time  $t$  is presented by the average of the vehicle speeds in the previous  $k$  frames, i.e., an average of speeds from  $t-k$  to  $t$ . The vehicle speed for each frame is considered by using the distance the vehicle moved in the associated time lapse, i.e.,  $d \cdot \Delta t$ .

### 3.2.5 Decision Support

A deterministic decision support model is established to identify intruding vehicle hazards in work zones. As shown in Figure 8, intruding vehicle hazards are determined in three threat levels, i.e., safe, cautious, and dangerous. The intrusion hazard awareness model starts the three-level monitoring when the detected vehicle is 250 feet from the work zone, i.e., the longitudinal distance ( $D$ ) from the vehicle to work zone is 250. The safe level is presented as the green region in Figure 8, where  $D > 0$ . The cautious level, which is the yellow region in Figure 8, represents the

vehicle that enters the work zone ( $D < 0$ ) but is still out of the closed work zone area. Finally, the dangerous level, which is the red region in Figure 8, indicates that the position of the vehicle is within the work zone taper.



**Figure 8 Intruding Vehicle Hazards**

For example, on a two-lane highway with a posted speed limit of 60 miles per hour, the transition area (or the buffer area) of the work zone should be at least 720 feet long according to the Manual on Uniform Traffic Control Devices (MUTCD) (FHWA 2009). With the proposed deterministic intrusion hazard awareness model, monitoring begins when  $D$  is 250 feet, which is about 11 seconds from the vehicle to the work zone activity area (the end of buffer area) when the vehicle is traveling at the posted speed. The model turns to the cautious level when  $D$  becomes smaller than 0, which is around 720 feet, i.e., around 8.2 seconds, to the actual work zone activity area. The model turns to the dangerous level once the vehicle violates the work zone taper, i.e., enters the transition area, which is around 4 seconds to warn workers and drivers before an intruding vehicle enters the activity area.

### 3.2.6 Experimental Results

To validate the proposed intruding vehicle awareness algorithm, tests with solid results have been performed. These tests consist of simulated tests and field tests. Videos that a) simulate intruding vehicle and late merge cases were taken on Georgia Tech’s Savannah campus and b) monitor traffic in actual work zones on I-95, have been used to test the developed intruding vehicle awareness algorithm.

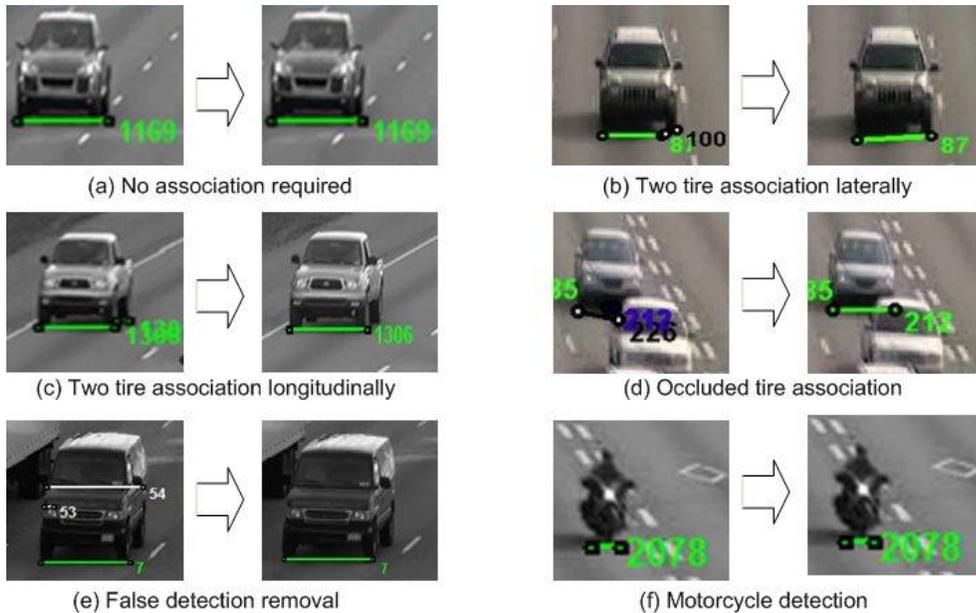
#### *Vehicle Detection and Tracking Test*

The vehicle tire detection method proposed in this study is designed to address the partial occlusion issues that are frequently seen in work zones. To assess the performance of the proposed tire detection method when partial occlusion is present, two sub-groups of images were used, including a low traffic volume condition with fewer occlusion cases and a high traffic volume condition with more occlusion cases. The two sets of images were collected on I-95 near Savannah, Georgia. The ground truth for the tires in each frame was manually digitized and further grouped into tires belonging to an occluded vehicle and tires belonging to a non-occluded vehicle. The automatic results were then compared with the ground truth. It can be observed in Table 1 that the proposed tire detection method demonstrates good tire detection rates from both image sub-groups with different traffic volume conditions (i.e. occlusion conditions), presenting the false negative (FN) rates of the front tires at 0.148% and 0.154% respectively. It is also observed that using the proposed method, there is no significant difference in detecting tires of an occluded vehicle or a non-occluded vehicle.

**Table 1 Tire Detection Experimental Test Results**

	Frames	# of Tires (All/Non-Occluded/Occluded)	FN Rates (All/Non-Occluded/Occluded)	FP Cases
Low Volume	2,433	16,890 / 13,994 / 2,896	0.148% / 0.150% / 0.138%	117
High Volume	2,101	48,672 / 38,924 / 9,748	0.154% / 0.149% / 0.174%	132

The same dataset was also used to evaluate the performance of the tire association and validation. It is noticed that there were several FP cases identified in the tire detection test. However, by applying the detection association and validation method, the FP cases listed in Table 1 were all eliminated. Figure 9 shows different tire detection cases that were improved by the tire association and validation. In Figure 9a, under the strong shadow of the bumper, the two individually detected tires are correctly grouped, and no tire association is needed in this case. In Figure 9b, the two tires, ID 87 (left tire) and ID 100 (right tire), are individually detected. Apparently, the lateral distance between the two detected tires is smaller than 8 ft., so these two detections are associated with the same vehicle. In Figure 9c, the two tires, ID 1306 (front tires) and ID 1201(rear tire), are individually detected. Through the association, the longitudinal distance from two detected tires is smaller than 10 ft., so these two detections are associated with the same vehicle. In Figure 9d, the vehicle at the back is partially occluded, and one of its tires is detected as ID 212 (left tire). By validating the vertical edge connected to the detection, the right occlusion case is identified. Therefore, the current tire detection is used to estimate the vehicle detection by extending the current detection to 8 ft. on the right. In Figure 9e, several false tire detections are produced, e.g. front light and edge of the windshield. By validating the vertical offset of the ground, these false detections are removed because the height was greater than 3 ft. In Figure 9f, the motorcycle is detected if the detected tire is isolated.



**Figure 9 Different Tire Detection Cases for Association and Validation**

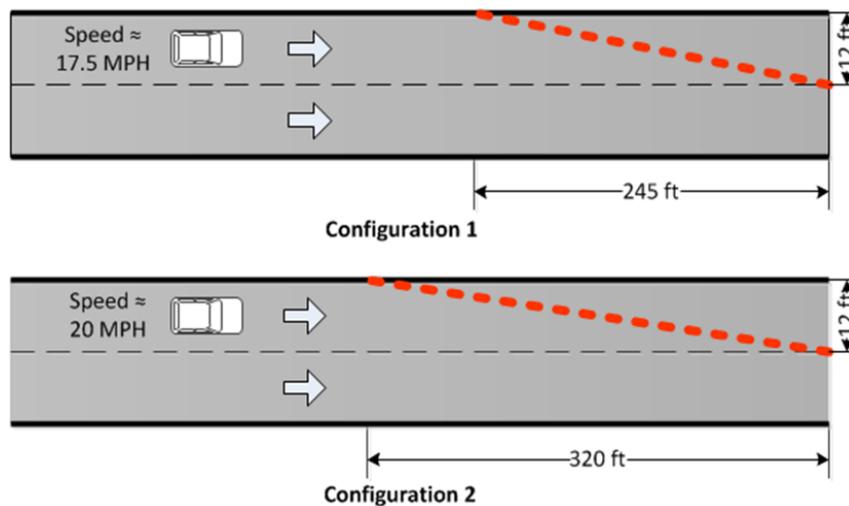
This test shows the detection association and validation effectively reduced all FP cases identified in the tire detection. Also, the proposed method accurately detected the partial occlusions and completed vehicle detection using the detection result of the non-occluded tire and other geometry information. Together with the tire detection, the proposed method effectively addresses the partial occlusion issues that remained a challenge in the previous study.

***Intruding Vehicle Awareness Test***

To validate the developed intruding vehicle awareness algorithm, an experimental test was conducted using a set of videos collected on Georgia Tech’s Savannah campus. A left-lane closure work zone was set up on a straight road (Figure 10) to simulate an actual work zone. Two transition area lengths (Figure 11) were used to simulate different work zone configurations.



**Figure 10 Intruding Vehicle Awareness Test Map**  
(Map Source: Google Maps)



**Figure 11 Work Zone Configurations for Intruding Vehicle Awareness Algorithm Test**

For each configuration, both intruding vehicle and late merge (vehicle merging within the transition area) cases were simulated. Three intruding vehicle and three late merge cases were simulated for each configuration. The developed intruding vehicle awareness algorithm successfully detected and tracked the vehicle in the six intrusion and the six late merge cases. The corresponding warning levels were also correctly detected. Figure 12 shows an example of the tested algorithm that correctly detected the intruding vehicle, and the warning level was successfully identified as dangerous since the vehicle was violating the work zone taper.



**Figure 12 Example of the Intruding Vehicle Awareness Algorithm Test Results**

### **3.2.7 Summary**

The intruding vehicle awareness algorithm was developed in this section. The detection of intruding vehicles was conducted using an innovative tire-based vehicle detection method proposed in this study. The vehicle tracking and surrogate extraction processes were also presented. The experimental results demonstrate the intelligence and reliability of the developed algorithm in detecting and tracking vehicles in work zones. Future study and analysis of vehicle trajectories as related to intrusion hazard awareness should be conducted. Moreover, communication and warning devices should be developed in future research.

## **3.3 MISSING TRAFFIC CONTROL DEVICE AWARENESS ALGORITHM**

This section first reviewed the need of missing traffic control device awareness systems, followed by a description of the developed work zone missing traffic control device awareness algorithm. The core of the algorithm, including traffic control device detection, tracking, and surrogate extraction, as well as the test results, are described below.

### **3.3.1 Review of Missing Traffic Control Device Awareness Algorithms**

According to GDOT's construction engineers, it is critical to maintain the integrity of traffic control devices in work zones. Traffic control devices play a critical role in maintaining the delineation of work zone areas and ensuring the safety of vehicles outside the work zone, as well as the workers inside the zone. However, traffic control devices, especially delineation devices, e.g., cones, barrels, etc., are often buffeted by swaying trucks or strong winds and

become “missing.” These missing traffic control devices can confuse drivers, especially at night, and lead to severe accidents in work zones. Currently, the detection of missing traffic control devices is determined by flaggers, project inspectors, contractors, or workers when they are present in the work zone. However, they cannot be on site twenty-four hours a day. Consequently, there is a need to develop a system that can monitor work zone tapers twenty-four hours a day, detect displaced or missing traffic control devices, and inform/warn responsible authorities to remedy the problem. As mentioned previously, image sensing technologies, which have been successfully applied in various fields, provide a reliable and intelligent means to implement such a system. Therefore, for the first time, a vision-based missing traffic control device awareness algorithm is proposed in this study.

### 3.3.2 Traffic Control Device Detection

The algorithm for missing traffic control device awareness is relatively simple compared to the intruding vehicle awareness algorithm, since, typically, traffic control devices, such as cones or drums, are static in the image sequence. Similar to the intruding vehicle awareness algorithm, the background modeling is used to differentiate foreground pixels from background pixels in the image. The missing traffic control device awareness algorithm, nevertheless, focuses on detecting pixels that change from background to foreground, i.e., traffic control devices being removed. In addition to the background subtraction, thresholding, and background update procedures, a confidence level was introduced to the algorithm to reflect the confidence of a pixel being a background pixel in the image. It is updated based on the motion detection differentiating foreground pixels from background pixels.

- If a pixel is classified as background, the background model is adaptively updated. The confidence level of this pixel adaptively increases since the new observation is taken into account.
- If a pixel is classified as foreground, the update of the background model is blocked and the confidence level of this pixel decreases. This confidence decrease reflects the fact that the real background may drift apart from the background model since the new observation is not taken into account.

The confidence level update process is shown below, where  $C_t$  is the confidence level of a pixel at time  $t$ ,  $\alpha_d$  and  $\alpha_i$  are the update decrements/increments, and  $\beta$  refers to the adaptive coefficient. These coefficients are determined in the research on a trial-and-error basis.

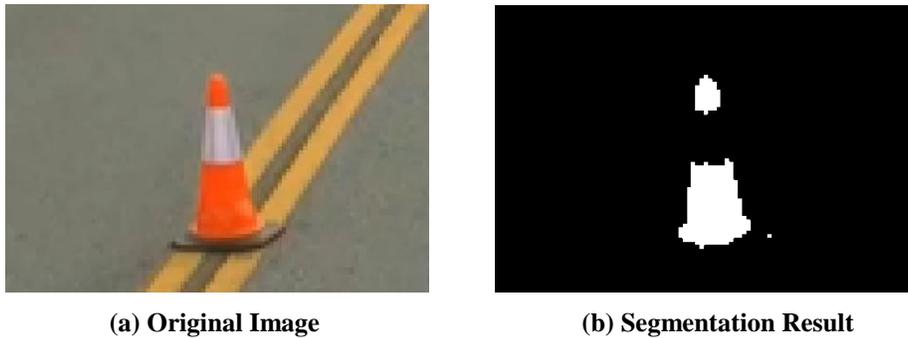
$$C_t = \begin{cases} \max(C_{t-1} - \alpha_d, 0), & \text{if foreground pixel} \\ \min(C_{t-1} + \beta \cdot \alpha_i, 100), & \text{otherwise} \end{cases} \quad (5)$$

Removing a traffic control device generates a long-term change in the background. When it occurs, since the observations do not match their background models, the confidence levels of the cone pixels decrease. When the confidence levels go below a certain threshold, a potential missing detection can be issued. The advantages of using the confidence levels rather than directly using the motion mask lies in the robustness to differentiate occlusion and short-term illumination changes from a missing traffic control device. In both cases (i.e. occlusion and short term illumination), false positive missing detections may be triggered using merely the motion mask.

While the background confidence level is a reliable feature to detect large, sudden, and stationary changes in the background, these large and sudden changes can also be caused by bright illumination condition changes that may lead to false positive detections. To reduce potential false positives, the HSV color segmentation module was proposed to enhance the detection, for all channelization devices, such as cones or drums, share one common characteristic: they all are orange. The hue-saturation-value (HSV) color space was selected in the algorithm to separate the orange color from other colors in the image, since it is not sensitive to illumination changes and is closer to the human perception of color than the other color spaces.

The Boolean condition for color segmentation is presented in the following equation, where  $x$  is the pixel position,  $H(x)$  is the hue value, and  $S(x)$  is the saturation value.  $H_{\min}$ ,  $H_{\max}$  and  $S_{\min}$  are the thresholds used. Figure 13 shows an example of the HSV color segmentation results.

$$\text{Orange}(x) = (H(x) \geq H_{\min} \text{ AND } H(x) \leq H_{\max} \text{ AND } S(x) \geq S_{\min}) \quad (6)$$



**Figure 13 HSV Color Segmentation Result**

### 3.3.3 Traffic Control Device Tracking

The tracking of traffic control devices is different than the vehicle tracking mentioned previously because traffic control devices are static in the image. Therefore, this algorithm deploys predefined regions of interest (ROIs) to track traffic control devices. Only pixels within the predefined ROIs are computed. This strategy is employed in order to reduce the complexity of the algorithm (the features are only computed for the ROIs) and the number of false alarms (only localized changes in the background model are considered). As shown in Figure 14, an ROI is a bounding rectangle of the cone in image. For each ROI, a surrounding region proportional to the ROI width is automatically defined. The surrounding region enables the definition of a slight cone displacement, i.e., a cone is determined as slightly moved if it is still included in the union of the ROI and its surrounding area. On the contrary, if a cone is moved out of the surrounding area, it is identified as a missing cone.



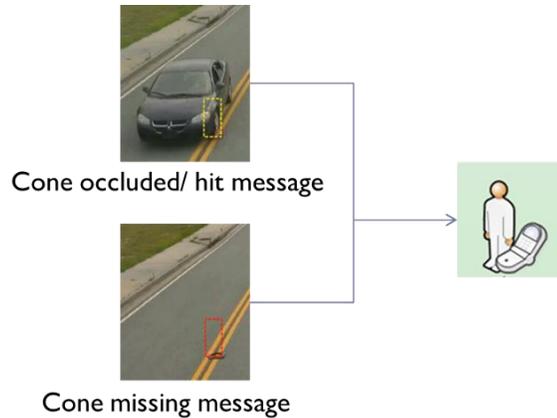
**Figure 14 Example of a Cone ROI and Its Surrounding Area**

### **3.3.4 Surrogate Extraction**

The surrogate for the missing traffic control device awareness is the status (e.g., present, occluded/moved, and missing) of each traffic control device. The status update model is the cornerstone of the developed algorithm. It is a robust way to validate a missing traffic control device while being unaffected by temporary occlusion and slight displacement. Each cone has a status associated with it. Three main statuses, including “present”, “missing” or “occluded/moved” could be assigned to each control device. “Present” is the initial status of the algorithm. Once the background confidence level inside the ROI identifies the presence of foreground pixels, the “missing” or “occluded/moved” statuses may be given. The “missing” status can be reached when the cone is missing from the ROI that can be verified by the background and the HSV color modules, i.e., a certain portion of the ROI becomes foreground pixels and no orange pixels are identified in the ROI. If the cone is still included in the surrounding region, but the orange color percentage remains reduced, the cone is said to be partially occluded or slightly moved, which becomes the “occluded/moved” status. If the cone is fully occluded, the major portion of the ROI area will be identified as foreground pixels, since the background pixels are covered by new foreground pixels; in the short term, it would be assigned as the “occluded/moved” status. Once the “occluded/moved” status is given, the “missing” status can also be reached if the occlusion is not validated by workers or if the duration of the “occlusion/moved” status has lasted longer than the predefined threshold (e.g., 20 seconds).

### **3.3.5 Decision Support**

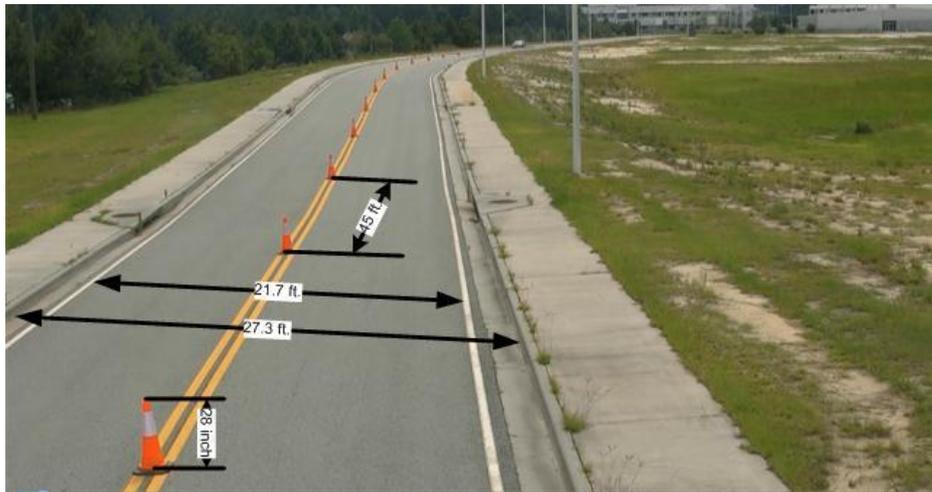
When a traffic control device is identified as “missing,” the proposed system will send out a message via a smart phone to the supervisor, who should be aware of the integrity of work zone traffic control devices. This notification will be sent with an image showing the missing traffic control device(s), and the supervisor can, therefore, verify the missing device condition and take proper action to remedy the problem immediately after he verifies the missing traffic control device condition, even if he/she is not in the work zone.



**Figure 15 Supervisor Notification via a Smart Phone**

### 3.3.6 Experimental Results

Different sequences have been used to validate the proposed algorithm. The image sequences, including actual situations in work zones, e.g., cone occluded by workers or vehicles, cone removed by workers or vehicles, cone slightly moved, etc., are generated in a simulated work zone at the Georgia Tech Savannah Campus as shown in Figure 16. There are twelve 28-inch cones regularly spaced. The distance between two consecutive cones is 45 ft. to simulate the 55 mph rural highway work zone.



**Figure 16 Scene Configuration**

The tested scenarios, as shown in Figure 17, include a) safe scenarios, such as Figure 17a in which the cone was slightly moved by a worker, Figure 17b in which the cone was temporarily occluded by a worker, and Figure 17c in which the cone was temporarily occluded by a truck; and b) missing traffic control device scenarios, such as Figure 17d in which the cone was removed by a worker, Figure 17e in which the cone was hit and knocked down by a vehicle, and Figure 17f in which the cone was removed by the truck. The developed algorithm was able to successfully detect all the missing traffic control device scenarios and issued no false positives when the cone was

only slightly moved or temporarily occluded. In addition, the developed algorithm successfully sent warning messages along with the missing control device image to the supervisor via a smart phone, as shown in Figure 18.



(a) Cone slightly moved by worker



(b) Cone temporarily occluded by worker



(c) Cone temporarily occluded by truck



(d) Cone removed by workers

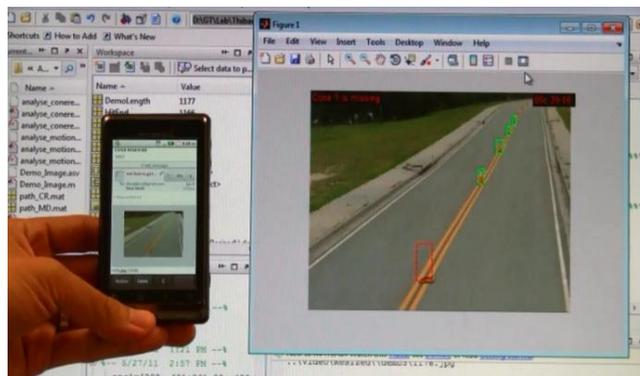


(e) Cone hit by a car



(f) Cone hit by a truck

**Figure 17 Test Scenarios for Missing Traffic Control Device Awareness Algorithm**



**Figure 18 A Missing Traffic Control Device Message Sent to Smart Phone**

### **3.3.7 Summary**

The missing traffic control device awareness algorithm has been developed and validated using control test data that simulates actual missing/occlusion traffic control device cases in work zones. The results indicate that the developed algorithm can reliably detect and update the status traffic control devices accurately. The algorithm can be integrated with communication technologies, such as wireless communication, smart phones, etc., to inform the supervisor of the need for adequate and timely response. Future studies could be conducted to advance the algorithm to be able to automatically detect control devices, which would reduce the manual workload.

## **3.4 POTENTIAL APPLICATIONS ON DRIVER BEHAVIOR STUDY**

As indicated previously, work zone safety is a pressing concern, and it has been intensified with the increasing number of roadway widening, rehabilitation, and reconstruction projects. To address this concern, many studies have been conducted, including identifying the work zone crash factors (Akepati and Dissanayake 2011; Klauer et al. 2006), performing the corresponding countermeasures (Kang and Chang 2006; Kwon et al. 2007), and developing hazard warning systems (Gordon et al. 2008; Li et al. 2007). However, due to a lack of methods to record and extract vehicle information and driver behaviors prior to the crashes that occurred, current studies have focused on corrective actions that highly rely on the police crash reports (Ullman et al. 2011). There is a need to increase the understanding of driver behaviors and the factors that lead to different driver behaviors in work zones. Therefore, in addition to the two developed algorithms, a 30-ft mobile work zone traffic data collection and monitoring tower was developed and used to collect actual work zone traffic data for studying driver behaviors in work zones.

### **3.4.1 Proposed Method**

The focus of this preliminary study is to identify different driver behaviors in closed lanes of work zones and the potential factors that lead to unsafe behaviors. Different driver behaviors in this study are determined using the merge location of vehicles in the closed lanes. Hence, to study drivers' merge behaviors in work zones, we divide the work zone transition area and the advance warning area (as indicated in Figure 19) into four zones to observe and classify vehicle merges at different locations. As illustrated in Figure 19, Zone 1 represents the whole work zone transition area; Zones 2, 3, and 4 cover the advance warning areas that are 0 ft. to 500 ft., 500 ft. to 1000 ft., and over 1000 ft., respectively. These distances refer to the distance from an upstream point to the beginning of the transition area. We used the mobile tower with its multi-view cameras to cover these four zones, as shown in Figure 20; Figure 20a focuses on Zones 1 and 2, and Figure 20b focuses on Zones 3 and 4.

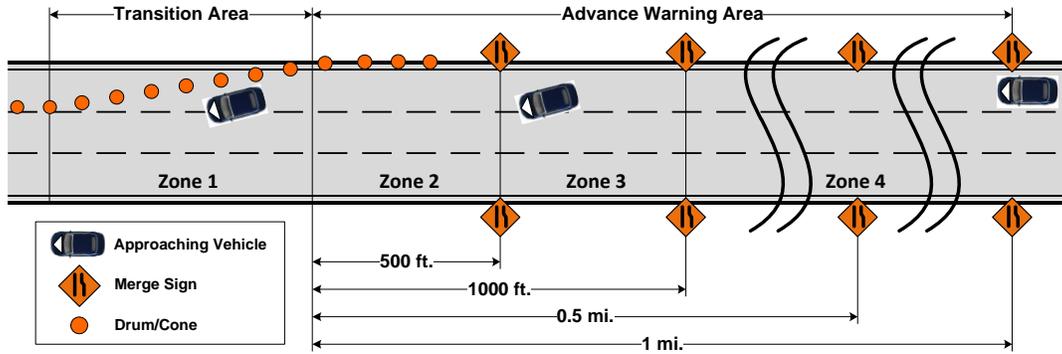


Figure 19 Four Zones Defined in the Advance Warning and Transition Areas



(a) Far view covering Zones 1 and 2

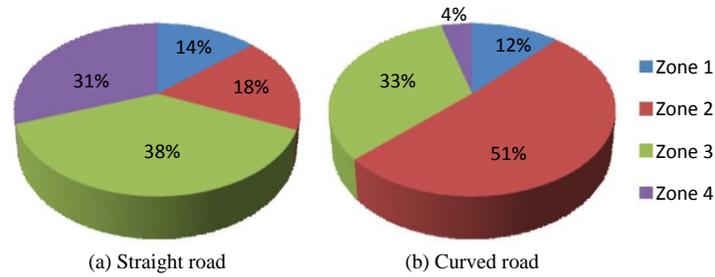
(b) Close view covering Zones 3 and 4

Figure 20 Example Images Captured by Multi-view Cameras on the Mobile Tower

### 3.4.2 Preliminary Results

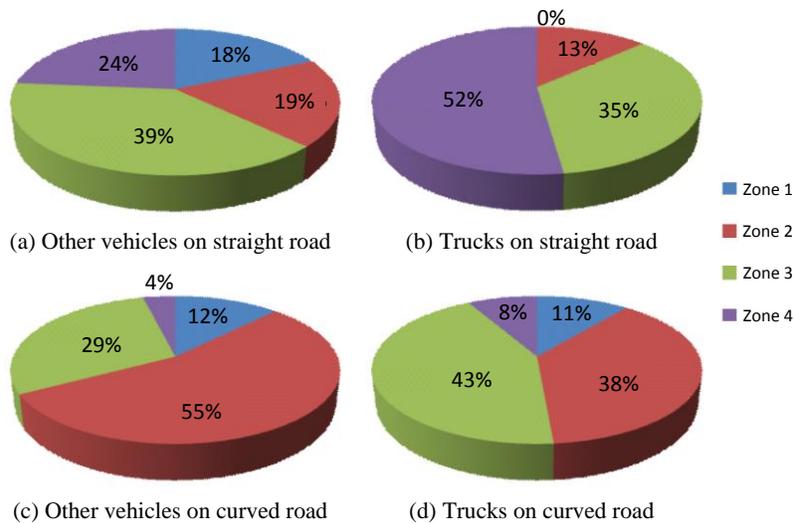
Two sets of 30-minute data collected in work zones on I-95 near Savannah, Georgia, in March 2011, were analyzed using the merge locations of vehicles in the closed lane in work zones. The two datasets were selected to help identify potential factors (e.g., roadway geometry and vehicle type) that may lead to different merge behaviors in work zones. The first dataset was collected on a straight road segment, and the second dataset was collected on a curved road segment, and both datasets were collected in the outside-lane of a one-lane closure work zone. The number of vehicles that merged in each of the four zones was recorded. Similar traffic conditions for the two datasets were selected during the 30-minute period of study; the first set of data, collected on the straight road, counted 927 vehicles, 95 of which were in the closed lane; the second set of data, collected on the curved road, counted 1,034 vehicles, 143 of which were in the closed lane.

The results indicate that vehicles' merge behaviors may be affected by different roadway geometries. As shown in Figure 21, a total 69% of the vehicles merged early in Zones 3 and 4 on the straight road segment. On the other hand, only 37% of the vehicles merged early in Zones 3 and 4 on the curved road segment. This may be caused by shorter sight distances or the presence of obstacles on a curved road, which would limit the sight distance of the driver.



**Figure 21 Merge Frequency at Different Zones under Different Roadway Geometry (Tsai et al. 2011)**

The same datasets were also analyzed based on different types of vehicles. Two types of vehicles were identified: truck and non-truck vehicles. Semi-trucks, recreational vehicles (RVs), and buses were classified as trucks, and all other vehicles were classified as non-trucks. The results reveal that for both segments, most trucks merged in Zones 3 or 4, yet a higher percentage of other vehicles merged in Zones 1 or 2. For example, Figure 22(c) depicts that among all non-truck vehicles observed in the closed lane on a curved road, 67% merged in Zones 1 or 2 and 37% merged in Zones 3 or 4; however, Figure 22(d) shows that among all trucks, 49% merged in Zones 1 or 2 and 51% merged in Zones 3 or 4. Based on our observation, we conclude that trucks tend to merge earlier (farther away from the taper) than other vehicles in the closed lane of work zones. The results might be because truck drivers have a better view and longer sight distance than non-truck drivers. More detailed outcomes are presented in another study (Tsai et al. 2011).



**Figure 22 Merge Timing/Location based on Different Vehicle Types (Tsai et al. 2011)**

### 3.4.3 Summary

The preliminary study results demonstrate the feasibility of using the developed 30-ft mobile traffic data collection and monitoring tower to study driver behaviors in work zones. Our preliminary results indicate that driver behaviors could be influenced by factors such as roadway geometry and vehicle type. Two findings were identified in the results: a) vehicles in work zones on a curved road, in comparison with those on a straight road segment, tend to merge later (i.e., closer to the taper.), b) trucks tend to merge earlier than non-truck vehicles in/near work zones.

Both findings lead to one potential causal factor: different sight distances. More comprehensive studies could be conducted to identify these factors to better understand driver behaviors in work zones and further enrich work zone safety and mobility studies. This study will also provide an effective means for engineers to quantitatively evaluate the performance of different traffic control devices, traffic control configurations, etc., to further derive guidelines for optimum work zone configurations under different conditions.

## 4. CONCLUSIONS AND RECOMMENDATIONS

In this study, a vision-based work zone hazard awareness methodology, along with two hazard awareness algorithms (an intruding vehicle awareness algorithm and a missing traffic control device awareness algorithm) and a 30-ft mobile traffic data collection and monitoring tower were developed. The key findings and conclusions are summarized below:

- **An intruding vehicle awareness algorithm.**

An intruding vehicle awareness algorithm has been developed in this research to detect vehicles intruding into work zones. An innovative, tire-based vehicle detection and tracking method has been proposed in this algorithm to address unique technical challenges, such as vehicle occlusions and changes of lighting conditions, and is introduced by using vision technology in work zones. The developed intruding vehicle awareness algorithm has been tested using a simulated work zone at Georgia Tech's Savannah campus. Intruding vehicles were detected reliably. In addition, the proposed algorithm has also been tested using an actual work zone on I-95 near Savannah, Georgia. These promising results indicate the developed algorithm can reliably detect and track intruding vehicles, and it is able to provide early warning to workers and drivers, which will greatly improve work zone safety. Additional tests are needed to refine the intruding vehicle awareness algorithm before actual implementation.

- **A work zone missing traffic control device awareness algorithm.**

A work zone missing traffic control device awareness algorithm has been developed for the first time in this research. This algorithm has been tested using simulated work zones at Georgia Tech's Savannah campus, and different scenarios involving missing/occluded control devices were simulated. All of the simulated missing traffic control device cases were successfully detected. There were no FN or FP cases in the test. A supervisor notification application to support the decision making model was also developed and tested; it successfully sent out a warning message with an image of the missing device to the supervisor via a smart phone. The test results indicate that the missing traffic control device awareness algorithm can reliably detect and track traffic control devices, identify missing control devices, and inform a supervisor to take adequate action to remedy the problem. Additional tests are needed to refine the missing traffic control device awareness algorithm before implementation.

- **A comprehensive vision-based work zone hazard awareness methodology.**

This research proposes a vision-based methodology that comprehensively detects potential work zone hazards, including intruding vehicles, missing traffic control devices, and, workers or machines (such as work trucks and paving machines) inside work zones. Although this research focuses on intruding vehicles and missing traffic control device awareness, it could be applied to other work zone issues. The methodology demonstrates the ability to provide early warning to workers and drivers, thereby significantly improving work zone safety. With the promising results of the two developed algorithms, we foresee that the proposed methodology can be applied to develop an integrated, intelligent work zone hazard awareness system.

- **A 30-ft mobile traffic data collection and monitoring tower.**

A 30-ft mobile tower that collects and monitors traffic data in work zones has been developed in this study. This tower was successfully used to collect work zone traffic data in an actual resurfacing work zone on I-95 near

Savannah, Georgia. The data collected was used to study driver merge behaviors in work zones affected by different roadway geometries and vehicle types. The preliminary results indicate that the developed mobile tower, along with computed vehicle trajectories, can be used to study driver behaviors under a variety of conditions, as well as the causal factors that impact work zone safety and mobility.

At this stage, with the issues identified in the literature review, this research has successfully developed an intruding vehicle awareness algorithm, a missing traffic control device awareness algorithm, and a 30-ft mobile tower to gather data and monitor work zone traffic. The developed algorithms will play a key role in the development of an intelligent, vision-based work zone hazard awareness and early warning system in the future. The implementation of the proposed methodology is expected to improve work zone safety and reduce the fatalities/injuries caused by intruding vehicles or missing control devices. Recommendations for future research are as follows:

- **Additional tests for validating and refining the developed algorithms.** Additional tests with different roadways, traffic conditions, and lighting conditions are needed to further test and refine the algorithms for field implementation.
- **Design and implement communication and warning hardware.** With the promising results of the two developed algorithms that intelligently and reliably detect intruding vehicles and missing traffic control devices, it is recommended that communication and warning system hardware be further designed and implemented to send timely warning messages to drivers, to trigger sirens and lights to warn drivers and workers, and to notify supervisors and/or emergency response units of potential hazards.
- **Extension of the study on work zone safety.** The developed algorithm for detecting intruding vehicles currently uses a deterministic model with three threat levels. It is recommended that an extended study be conducted to develop a probabilistic model (based on the analysis of the extracted vehicle trajectories) that reliably predicts intrusions to provide early warnings to drivers and workers.
- **Extension of the study on work zone mobility.** In the developed intruding vehicle awareness algorithm, traffic information/surrogates, such as the distance, speed, and trajectory of a vehicle, were calculated and extracted for work zone safety studies. It is also recommended that algorithms that extract additional surrogates, such as vehicle gaps, headways, and traffic density, be developed.
- **Evaluation of the work zone configuration performance.** It is recommended that a follow-up research project using the developed 30-ft mobile work zone traffic data collection and monitoring tower to gather work zone data that can be used to quantitatively evaluate the performance of work zone traffic control devices, work zone configurations, and driver behaviors. Based on the analysis of the collected data, engineers can further derive guidelines for optimum work zone configurations under different conditions to ensure work zone safety and mobility.

## 5. PLANS FOR IMPLEMENTATION

With the promising outcomes, the principal investigator is working GDOT and US DOT to initiate a research project to apply and implement the vision-based algorithms developed in this project. The vision-based algorithms will be further integrated with non-vision sensors (e.g., sonar, infrared, laser, etc.) to provide a reliable means to detect unsafe driver behaviors. A control station will be developed to synchronize data collected from vision and non-vision sensors, process and extract useful information (such as traffic speed, traffic volume, driver behaviors, etc.), and send signals to trigger the feedback devices, making drivers be aware of their unsafe behaviors. A wireless communication system will also be developed to provide real-time communication between the control center, sensors, and warning/feedback devices. Simulated and field tests will be conducted to study driver behaviors and quantitatively evaluate the performance of the proposed real-time unsafe driver behavior feedback system.

Based on the plan, the key concerns and requirements of the system implementation are as follows:

- **Real-time system development.**

To implement the system, a real-time program is required. The algorithms developed in this study will be developed in real-time enabled environments (e.g., C++) and tested thoroughly. The algorithms, including data acquisition, data processing or extraction, and communication, will be practical to enable implementation into a real-time system.

- **Sensors and communication devices integration.**

In addition to the software, the hardware, i.e., sensors, communication devices, and warning devices, will be developed and integrated. A control station that integrates information collected from sensors and feeds information into communication and warning devices is needed. Technologies for the communication and warning components are mature, and it is feasible to integrate the required hardware to support real-time work zone operations.

- **Data synchronization and processing.**

The data synchronization and processing is a crucial key for providing accurate and real-time information for the decision making process of the system. Algorithms that efficiently synchronize data collected by different sensors and extract useful information will be developed.

- **Excessive and comprehensive tests.**

Excessive and comprehensive tests are the key to provide solid evidence of the system capabilities. Tests will be conducted to evaluate the performance of the developed system. Close interactions with GDOT engineers will be undertaken; their professional experiences and suggestions will help refine and practically implement the developed system.

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