Feasibility of GPS-based Warning System for Roadside Workers

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***Abstract*—Roadside workers and emergency responders, such as police and emergency medical technicians, are at significant risk of being struck by vehicular traffic while performing their duties. While recent work has examined active and passive systems to reduce pedestrian collisions, current approaches require line of sight using either laser, infrared, or vision based systems. We address this problem by developing a GPS-based solution that equips roadside workers and vehicles with GPS units to estimate the trajectory of oncoming traffic, and estimate whether worker strike is imminent. The results of our study show that our approach is 91% accurate in alerting the worker and vehicle of collisions and near misses. Furthermore, accurate warnings can be provided 5-6 seconds before any potential collision, allowing time for mitigating solutions.**

I. Introduction

Every day there are thousands of roadway workers that must perform their duties near passing motorists in both defined work areas, such as traditional work zones with barricades, cones, well-informed signage, and undefined work areas, such as roadside events with limited or no signage. These roadway workers include construction crews, public safety workers, survey crews, and roadway clean-up/mowing personnel. Each year more than 20,000 injuries and more than 100 fatalities occur at road construction zones. Nearly two-thirds (62 percent) of these incidents involved a worker being struck by a construction vehicle [1]. Public safety (e.g., police and firefighters) personnel are at a particular risk for being struck by passing vehicles. According to the Bureau of Labor Statistics (BLS), about 18 percent of police officer fatalities from 1992-1997 were due to officers being struck by vehicles while issuing traffic citations or performing duties on the roadway [2].

Significant efforts have examined active and passive measures to reduce vehicle and pedestrian incidents [3]. Common approaches include using computer vision with visual [4] and infrared cameras [5], and laser range finders [6], [7] to estimate the presence and distance to pedestrians. While these approaches are successful, they can be limited due to roadway occlusions such as trees, cars, or weather that restrict the visible range of the camera [8]. Laser and radar systems can address these issues, but have more difficulty distinguishing between pedestrians and other roadway objects [9]. Furthermore, these systems require line-of-sight to the target and may not protect the roadside worker that is around a bend in the road or over an oncoming hill.

Given these concerns, our work explores the role of GPS in estimating potential collisions between vehicular traffic and roadside workers. We propose equipping roadside workers and vehicles with small GPS receivers where their positions will be exchanged using dedicated short range communications (DSRC). These positions will be used to calculate the likelihood of a potential collision by estimating how close the vehicle will pass to the worker at some future time. GPS units can easily be integrated into production vehicles, and new, smaller GPS units could be used to create wearable safety solutions for roadside workers. While positions provided by GPS are less accurate than visual or laser-based systems, they are not affected by roadway occlusions or environmental factors. Furthermore, by equipping roadway workers and vehicles with DSRC-equipped GPS, both parties can independently determine a collision likelihood and take corrective action.

We examine the feasibility of GPS-based pedestrian collision detection by performing trials on an integrated testbed for vehicle-to-infrastructure and vehicle-to-vehicle technologies located at the author's university. Three test cases were evaluated in which a collision, near miss, and clear miss of a pedestrian was simulated using roadside GPS and DSRC units. From this data, a warning system was developed to determine the accuracy of predicting worker-vehicle collisions using solely GPS positional data. The results indicate that a correct warning can be issued 91% of the time and with approximately 5-6 seconds notice.

II. Motivation and Related Work

Working alongside motorways and highways is dangerous. Examining injuries on highway construction projects in New York between 1993-1997, Bryden and Andrew found that 15% of all serious injuries were caused by vehicle accidents, two-thirds of which were caused by vehicles straying into the workzone [10]. These areas are also dangerous for law enforcement officers and emergency responders. From 2001-2010, there were 118 law enforcement officers who were struck by a vehicle and killed. Of these 118 deaths, 37 percent occurred during duties like traffic stops and road blocks while the majority (63 percent) occurred while directing traffic or assisting motorists along the roadway [11]. The BLS also estimates that approximately six percent of firefighter fatalities from 1992-1997 resulted from being struck by a vehicle while either directing traffic or conducting roadside emergency rescues [2].

With the advent of intelligent transport networks, new technologies have been created to address roadway injuries and fatalities such as adaptive cruise control, lane departure warnings, and automatic braking for collision avoidance [3]. Specific to reducing pedestrian injuries are computer vision approaches that scan the path of the vehicle for pedestrians. Once detected the driver can be alerted, automatic breaking applied, or autonomous evasion maneuvers taken by the vehicle [12], [13]. Stereo cameras have been used to provide a 3-D forward view of the road [8], [14], while multiple cameras around the vehicle can create a birds-eye-view of the surrounding area to aid in parking lots or other areas where pedestrians may approach from multiple directions [4].

Like all computer vision applications these approach can suffer from roadway occlusions such as trees, building, or other vehicles on the road [7], [8]. Specific to our problem of detecting roadway workers, work zones can have significant clutter due to construction vehicles, materials, and movable barriers. Part-based classification has been attempted to recognize “parts” of a pedestrian rather than a whole person to deal with occlusions [15] as well as models of pedestrian movement to distinguish people from other objects [16]. Infrared cameras can also be used to detect the “heat signatures” of pedestrians [6], [9]. Laser and radar systems have also been used as they provide highly accurate ranges (up to 135 m at ± 5 cm) to forward targets [7]. However these systems can often be confused by the multitude of objects due to ground clutter.

While all these approaches can be highly accurate (85% to 100% at 35 m [8]) they all require line-of-sight to the target for detection. Roadside workers that are occluded by dense traffic, construction materials, or around a curve or hill in the road, will not be detected. Thus we propose to equip roadside workers and vehicles with GPS units and enable them to share position information over dedicated short range communications. These local networks can be used in conjunction with exiting approaches to protect a new class of pedestrians. Additionally, having both vehicles and roadside workers in the detection processes enables both parties to develop their own warning estimates and take independent corrective action. While GPS positions are less accurate than existing approaches (approximately 2.5 m for 50% of positions [17]), we will show in this work how on straight segments of road a GPS-based system can distinguish between collisions, near-misses, and total misses with 91% accuracy. This work is largely a feasibility study and uses the simple case of a straight segment of road and does not address the more complex issue of curved roadside detection.

III. Problem Formulation and Solution

In this section we outline our model for estimating roadside worker and car collisions. The primary metric is to determine how close a vehicle will approach the worker with sufficient time to provide a warning to the driver or the worker. We have assumed that both the worker and the vehicle can know their position via GPS and exchange information over some radio network. Also, to simplify our calculations, this model is only valid for a relatively straight segment of road. Given these assumptions, we can visualize this scenario in Figure 1 where a moving vehicle is approaching a worker. The blue dots represent the known positions of the worker and vehicle.

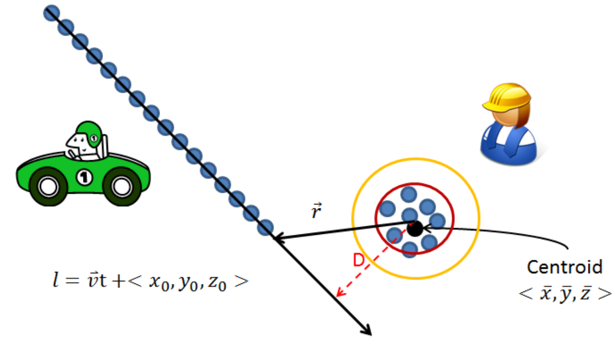

Fig. 1: Model of Worker Car Collision. Blue dots show the positions of the worker and vehicle. Yellow and Red circles indicate the Warning and Alert distances from the worker.

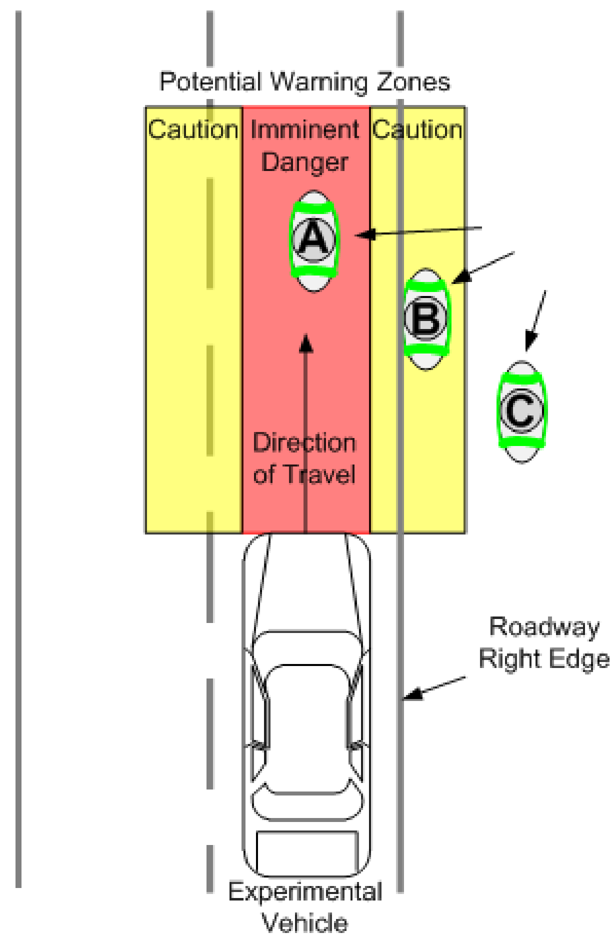

Fig. 2: Three Experimental Scenarios - A (Collision), B (Warning), and C (None)

A. Problem Definition

To warn the worker about a potentially dangerous condition, the trajectory of the car must be estimated and compared to the position of the worker. We assume that both the worker and the vehicle know the position of each other and can estimate their approach distance. If the car is estimated to approach too close then an Alert will be issued telling the worker of an impending danger. If the car will pass close to the worker, but not at a dangerous distance, a Warning will be issued. These alerts/warnings are determined by comparing the linear distance between the vehicle trajectory and the average position of the worker. In Figure 1 the trajectory of the car is given by $\vec{v}$ and the position of the worker by $(\bar{x}, \bar{y}, \bar{z})$. Given some vector $\vec{r}$ between the worker and the trajectory $\vec{v}$, the shortest distance between the two is simply: $d = \frac{||\vec{r} \times \vec{v}||}{||\vec{v}||}$

From the exemplar in Figure 1, if the car would pass close to the worker, within the yellow radius, a Warning would be issued. If the car passed within a dangerous proximity, within the red circle, an Alert would be issued. If the vehicle did not pass close to the worker, no alert would be issued. Figure 2 shows a top-down view of the areas where an Alert or Warning would be issued. These distances are indicated by the red and yellow circles around the worker. In the remainder of this section we will outline the required calculations to implement this warning system.

B. Estimating Vehicle-Worker Collisions

This section outlines the required calculations to implement the warning system described in the previous section. We discuss preliminary calculations needed to transform GPS coordinates (ϕ, λ, H) into a more tractable Cartesian system (X,Y,Z). Also, we describe the required calculations to determine the location of the worker, vehicle trajectory, and estimated worker-vehicle distance. Finally, a collision detection algorithm is presented based upon these calculations. Table I outlines parameters used for these calculations and provides their default values used in our experiment.

Conversion to Cartesian Coordinates: When using GPS systems, the position of an object is frequently represented in terms of Latitude (ϕ), Longitude (λ), and Altitude (H). For our collision detection algorithm, these positions must be converted into a 3-D Cartesian position (X,Y,Z) to allow for more tractable computation of the vehicle trajectory and distance. The equations below provide the necessary steps to transform between the two coordinate systems. Please note the difference between h, which is altitude relative to an ellipsoid centered inside the Earth, and H which is altitude relative to mean sea level [18]. The values, $e^2 = 6.69437999014 * 10^{-3}$, and $a = 6378137$, are the eccentricity of the Earth and the length of its semi-major axis. The function ellipsoidSeperation is a table defining the relative position between Earth altitude (H) and ellipsoid altitude (h) at different points on the Earth's surface. These equations are adapted from [19].

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} (N(\phi) + h)\cos(\phi)\cos(\lambda) \\ (N(\phi) + h)\cos(\phi)\sin(\lambda) \\ (N(\phi)(1 - e^2) + h)\sin(\phi) \end{bmatrix} \tag{1}$$

$$N(\phi) = \frac{a}{(1 - e^2 \sin^2(\phi))^{1/2}} \tag{2}$$

$$h = H + ellipsoidSeperation(\phi, \lambda) \tag{3}$$

Determining Worker Position: The position of the worker is calculated as the centroid (average) of its last known positions. From Table I positions are remembered for the last t_{worker} seconds. A larger value of t_{worker} is good for stationary objects, but will become inaccurate if the worker moves around. To calculate the worker position, simply take the average of known positions as shown below. There will be $n = t_{worker} * f_w$ values based upon the frequency of position updates from GPS and memory of the worker.

$$(x_w, y_w, z_w) = (\sum_{i=1}^{n} \frac{x_i}{n}, \sum_{i=1}^{n} \frac{y_i}{n}, \sum_{i=1}^{n} \frac{z_i}{n}) \tag{4}$$

Determining Vehicle Trajectory: The trajectory of the vehicle is determined by finding the best-fit vector from the most recent vehicle points. This vector is found using Single Value Decomposition and requires more computation than that of the worker calculations. Equations (5) through (9) describe this process.

Let $\mathbf{X}$ be a matrix that holds the positions of the vehicle over the last $t_{vehicle}$ seconds. This matrix will have $n = t_{vehicle} * f_v$ rows where each row is a position of the vehicle in 3-space (x,y,z).

$$\mathbf{X} = \begin{bmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ ... & ... & ... \\ x_n & y_n & z_n \end{bmatrix} \tag{5}$$

We will use Single Value Decomposition to determine a vector ($\vec{v}$) that is the best fit through the points in $\mathbf{X}$. Calculate the mean position of the vehicle (x_v, y_v, z_v) such that:

$$(x_v, y_v, z_v) = (\sum_{i=1}^{n} \frac{x_i}{n}, \sum_{i=1}^{n} \frac{y_i}{n}, \sum_{i=1}^{n} \frac{z_i}{n}) \tag{6}$$

Subtract (x_v, y_v, z_v) from each row of $\mathbf{X}$ to create a new matrix $\mathbf{A}$:

$$\mathbf{A} = \mathbf{X} - \begin{bmatrix} x_v & y_v & z_v \\ ... & ... & ... \\ x_v & y_v & z_v \end{bmatrix} \tag{7}$$

Perform SVD on $\mathbf{A}$ to generate matrices $\mathbf{U}$, $\mathbf{S}$, and $\mathbf{V}$. Our implementation used MATLAB using the syntax shown in equation 8.

$$[\mathbf{U}, \mathbf{S}, \mathbf{V}] = svd(\mathbf{A}, 0) \tag{8}$$

The columns of $\mathbf{V}$ are vectors that fit $\mathbf{A}$. To determine the correct vector, examine the diagonal of $\mathbf{S}$ and find the value that is maximal, noting the column that the value appears in. Extract the same column from $\mathbf{V}$ to get our best fit vector

Parameter Symbol	Default Value	Description
d_{mon}	100m	Distance at which the worker begins monitoring the position of the car.
d_{warn}	12ft / 3.65m	Approach distance between the car and worker where a warning should be issued.
d_{alert}	6ft / 1.82m	Approach distance between the car and worker where an alert should be issued.
t_{worker}	30s	Length of time the worker will remember his previous positions.
$t_{vehicle}$	10s	Length of time the worker will remember the position of the vehicle.
f_v	10hz	The frequency at which the vehicle updates and transmits its position.
f_w	10hz	The frequency at which the worker updates and transmits its position.

TABLE I: Collision Detection Parameters

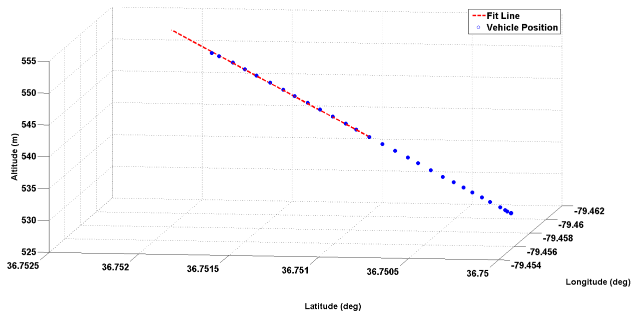

Fig. 3: Line fitted to sample vehicle positions.

$\vec{v}$. More formally, calculate $s^*_{i,j} = max(\mathbf{S}_{1,1}, \mathbf{S}_{2,2}, \mathbf{S}_{3,3})$, then $\vec{v} =< \mathbf{V}_{1,j}, \mathbf{V}_{2,j}, \mathbf{V}_{3,j} >$. $\vec{v}$ is now the best fit vector through the data in $\mathbf{X}$. A line can now be defined using $\vec{v}$ and (x_v, y_v, z_v) that fits the data:

$$l = \vec{v}t + (x_v, y_v, z_v) \tag{9}$$

The vector $\vec{v}$ will be used to estimate the vehicle trajectory and the future distance to the worker. Figure 3 shows an example of this process where the red line is a linear fit to a segment of the data shown in blue.

Calculating Vehicle-Worker Distance: From the preceding sections we have calculated the mean worker position (x_w, y_w, z_w) using equation (4), the vehicle mean position (x_v, y_v, z_v) using equation (6) and the a vector $\vec{v}$ estimating the vehicle trajectory using equations (5) to (9). Here we use those calculations to estimate the future distance between the worker and the car. Create a vector $\vec{r}$ that connects the worker centroid to the vehicle centroid as in equation 10. The distance between the car and the worker is estimated using equation 11.

$$\vec{r} = (x_v, y_v, z_v) - (x_w, y_w, z_w) \tag{10}$$

$$d = \frac{||\vec{r} \times \vec{v}||}{||\vec{v}||} \tag{11}$$

These calculations can be combined to create a collision detection algorithm to estimate the likelihood of a worker-vehicle collision. Algorithm 1 combines the previous calculations into a collision detection approach. The positions of the worker, vehicle, and the trajectory of the car are repeatedly updated to determine their likely approach distance. Depending on the estimated approach, an Alert or Warning is issued. Otherwise the algorithm does nothing.

Algorithm 1 Collision Detection Algorithm

```
Convert all (φ, λ, H) into (X, Y, Z).
(x_w, y_w, z_w)=CALCULATEWORKERCENTROID
(x', y', z')=GETMOSTRECENTVEHICLEPOSITION
d = ||(x_w, y_w, z_w) − (x', y', z')||
if d ≤ d_mon then
    v⃗ = CALCULATECARTRAJECTORY()
    d_approach=ESTIMATEAPPROACHDISTANCE
    if d_approach ≤ d_alert then
        Issue Alert
    else if d_approach ≤ d_warn then
        Issue Warning
    else
        Do Nothing.
    end if
end if
```

IV. EXPERIMENTAL SETUP

To evaluate our warning system, data was collected using a 2.2 mile integrated testbed for vehicle-to-infrastructure and vehicle-to-vehicle technologies located at the author's university. Two DSRC radios were used for the study, one attached to the test vehicle and another that was placed alongside the road to simulate our "worker". Each DSRC unit had GPS, DGPS, and could exchange messages with one another. DGPS was used to establish ground truth regarding how close the worker and vehicle approached.

For this experiment three test cases were devised: 1) a dangerous condition where the vehicle would strike the worker, 2) a warning condition where the vehicle would pass sufficiently close to the worker to be concerning, and 3) a negative condition where the vehicle was sufficiently far away so as not to pose a danger to the worker. These three positions are indicated in Figure 2 by the A, B, and C indicators. For Condition A the vehicle passed directly over the "worker" DSRC radio. To test this situation without damaging the DSRC, a boom was attached to the test vehicle that extended four feet from the vehicle. This configuration allowed the test vehicle to "run over" the radio without damaging the DSRC unit. Figure 4a shows the boom extending from the test vehicle with the "worker" DSRC in the foreground.

In Condition B the worker radio was moved to the edge of the road. For Condition C the DSRC was moved 12-15 feet off the roadside. For each condition the test vehicle was driven past the "worker" unit three times. The vehicle would begin down the road approximately 500 m away, would accelerate to 35 MPH, and drive in the lane until it passed the worker. Once the worker was passed, the vehicle would decelerate and

Intended/Actual	Warning	Alert	None	Precision	Recall
Warning	304	71	0	0.81	1.0
Alert	0	519	0	1.0	1.0
None	50	0	396		

TABLE II: Warning System Confusion Matrix with Precision and Recall for Warning and Alert Conditions.

return for another trial. Each trial took approximately 30 s. The tests are as shown in Figure 4.

On-board video, vehicle diagnostics, and position information was stored during the trial and analyzed afterwards to determine accuracy of the warning system. Accuracy is defined as providing the correct response based upon the parameters in Table I. Three passes by the vehicle were conducted for each position (A-C) creating nine trials overall. Two experiments were conducted in January and February of 2014 providing 18 trials overall. The results presented in this study combine both datasets.

V. Results

Position data was collected during two experiments in January and February 2014 using the setup described in Section IV. The data was evaluated offline using Algorithm 1 to determine the feasibility of using GPS to estimate worker-vehicle collisions. For each trial run the warning system would issue a response once per second based upon the estimated approach distance of the worker and vehicle. These responses were compared to the actual approach distance as determined by DGPS. Table 1 shows the confusion matrix generated by the warning system and compares the intended responses of the system to the actual ones that should have been issued. Precision and recall for the Warning and Alert conditions is reported as well.

Overall Results: The warning system exhibited 91% accuracy for all test conditions, where accuracy is defined as the percentage of time the system issued the correct response. When an inaccuracy occurred the system would under-estimate the approach distance, resulting in a more severe warning than was actually neccessary. For example, in 50 cases no alert should have been issued, but the distance between the worker and vehicle was under-estimated and a warning was issued. Similiarly, in 71 cases a Warning should have been issued, but a more severe Alert was produced. While the system was inaccurate at times, it did not fail to recognize the approach of a car within the warning distance.

For each data point in Table II, the error in the approach estimator was calculated and is plotted in Figure 5. This figure plots closest worker-vehicle approach distance determined with DGPS versus the estimation approach error. For a perfect estimator all data points would on the horizontal axis. In this figure most points lie below the axis, indicating our approach will typically under-estimate the worker-vehicle distance.

Performance Factors: Analyzing the data in more detail, several factors affected the accuracy of the results: occlusion of the worker GPS resulting in loss of position accuracy, and changes in the vehicle trajectory by the driver. When analyzing the January 2014 data it was observed that the worker GPS position had a larger distribution that was anticipated. It was theorized that a vehicle parked near the worker DSRC had occluded several GPS satellites, resulting in a loss of precision. This concern was noted in the February tests with all vehicles being kept further away and resulted in more accurate worker positions. The less precise data was retained for the study as occlusions of GPS satellites may be common in real-world applications of the warning system.

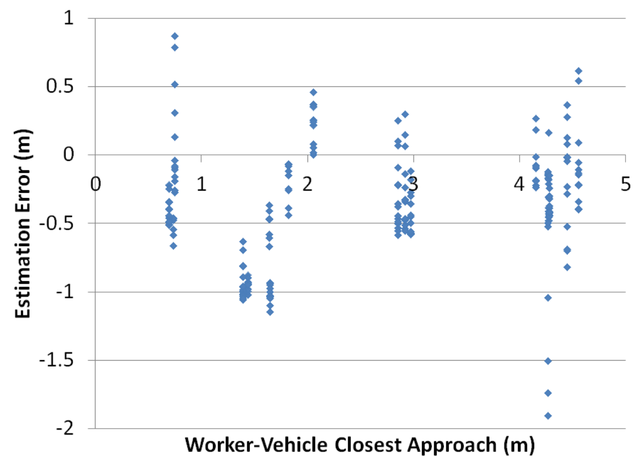

Fig. 5: Linear estimator error when predicting closest approach of vehicle and worker.

Another experimental factor was sudden variations of the vehicle trajectory either due to the driver or the condition of the road. To allow for testing Condition A in Figure 2, the test vehicle radio was attached to a boom extending off the side of the vehicle by four feet. Using the boom, the vehicle could "run over" the worker in Condition A without striking the "worker" radio. In a few cases the test vehicle would "bounce" causing a displacement in its position. A likely location for the error is when the vehicle transitioned between the bridge and roadway in the background of Figure 4b.

Impact of Monitoring Distance on Accuracy: A key parameter for the warning systems is the distance between the vehicle and the worker at which warnings are issued. This parameter, d_{mon} in Table I, was initially set to 100 m for our analysis. At our test speed of 35 MPH, warnings issued at 100 m would provide approximately 6-7 seconds of notice. The greater the distance the warnings are issued, the more time corrective measures can be taken. However, greater distance allows for more time for the car trajectory to vary, and predictions made at great distance may be inaccurate. Figure 6 compares the accuracy of the responses provided with the amount of time before the car approaches the worker at a constant speed of 35 MPH. Warnings provided 10s before the worker and vehicle pass are 91% accurate, but the accuracy quickly falls off as warning time (and consequently warning distance) is increased.

VI. Conclusion

A GPS-based collision detection algorithm for vehicle-pedestrian strikes has been presented. This initial study examined whether solely GPS positions could be used to estimate the approach distance between a roadside worker and an oncoming car. Experimental results show that the warning

(a) Boom extension to test condition A with "worker" DSRC shown in the road.

(b) Testing location looking towards the vehicle starting position. Worker DSRC shown in foreground.

Fig. 4: Experimental setup showing vehicle boom and test site.

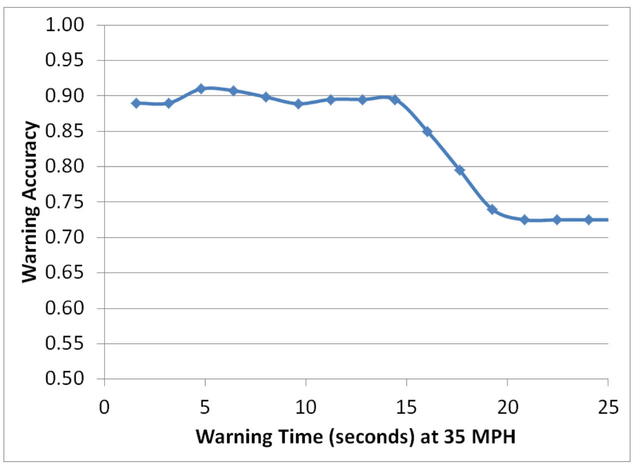

Fig. 6: Warning times and accuracy at 35 MPH.

system can distinguish between a near-miss, complete miss, and collision with a worker with 91% accuracy. Our approach enables detection of roadside workers in situations where existing solutions may fail due to visual occlusions or enivornmental conditions. Future work will focus on creating wearble garments for roadside workers and providing proper responses to drivers to avoid collisions. Additionally, sensor fusion using site-based DGPS or wearable intertial measurement units for workers may improve location accuracy. Finally our collision detection methods will be extended to more complex road segments and will allow for greater protection scenarios for roadside workers.

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References

[1] F. H. Administration, "Worker safety," http://www.ops.fhwa.dot.gov/wz/workersafety/index.htm, 2014.

[2] C. Clark and M. Zak, "Fatalities to law enforcement officers and firefighters, 1992-97," *Compensation and Working Conditions*, pp. 3–7, 1999. [Online]. Available: http://www.bls.gov/opub/mlr/cwc/fatalities-to-law-enforcement-officers-and-firefighters-1992-97.pdf

[3] D. Geronimo, A. M. Lopez, A. D. Sappa, and T. Graf, "Survey of pedestrian detection for advanced driver assistance systems," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 7, pp. 1239–1258, 2010.

[4] M. Gressmann, G. Palm, and O. Lohlein, "Surround view pedestrian detection using heterogeneous classifier cascades," in *14th International IEEE Conference on Intelligent Transportation Systems*, Oct 2011, pp. 1317–1324.

[5] Y.-C. Lin, Y.-M. Chan, L.-C. Chuang, L.-C. Fu, S.-S. Huang, P.-Y. Hsiao, and M.-F. Luo, "Near-infrared based nighttime pedestrian detection by combining multiple features," in *14th International IEEE Conference on Intelligent Transportation Systems*, Oct 2011, pp. 1549–1554.

[6] M. Bertozzi, A. Broggi, A. Fascioli, T. Graf, and M. Meinecke, "Pedestrian detection for driver assistance using multiresolution infrared vision," *IEEE Transactions on Vehicular Technology*, vol. 53, no. 6, pp. 1666–1678, 2004.

[7] S. Gidel, P. Checchin, C. Blanc, T. Chateau, and L. Trassoudaine, "Pedestrian detection and tracking in an urban environment using a multilayer laser scanner," *IEEE Transactions on Intelligent Transportation Systems*, vol. 11, no. 3, pp. 579–588, 2010.

[8] S. Nedevschi, S. Bota, and C. Tomiuc, "Stereo-based pedestrian detection for collision-avoidance applications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 10, no. 3, pp. 380–391, 2009.

[9] J. Ge, Y. Luo, and G. Tei, "Real-time pedestrian detection and tracking at nighttime for driver-assistance systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 10, no. 2, pp. 283–298, 2009.

[10] J. Bryden and L. Andrew, "Serious and fatal injuries to workers on highway construction projects," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1657, 1999.

[11] F. B. of Investigation, "Uniform crime reports: Officers accidentally killed (table 63)," http://www.fbi.gov/about-us/cjis/ucr/leoka/leoka-2010/tables/table63-leok-accidentally-circumstance-by-assignment-01-10.xls, 2010.

[12] C. G. Keller, T. Dang, H. Fritz, A. Joos, C. Rabe, and D. M. Gavrila, "Active pedestrian safety by automatic braking and evasive steering," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1292–1304, 2011.

[13] E. Coelingh, A. Eidehall, and M. Bengtsson, "Collision warning with full auto brake and pedestrian detection-a practical example of automatic emergency braking," in *13th International IEEE Conference on Intelligent Transportation Systems*. IEEE, 2010, pp. 155–160.

[14] C. G. Keller, M. Enzweiler, M. Rohrbach, D. Fernandez Llorca, C. Schnorr, and D. M. Gavrila, "The benefits of dense stereo for pedestrian detection," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1096–1106, 2011.

[15] A. Prioletti, A. Møgelmose, P. Grislieri, M. Trivedi, A. Broggi, and T. B. Moeslund, "Part-based pedestrian detection and feature-based tracking for driver assistance: Real-time, robust algorithms and evaluation," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 3, pp. 1346–1359, 2013.

[16] C. G. Keller, C. Hermes, and D. M. Gavrila, "Will the pedestrian cross? probabilistic path prediction based on learned motion features," in *Pattern Recognition*. Springer, 2011, pp. 386–395.

[17] u blox, "u-blox 7 gnss chip," http://www.u-blox.com/images/downloads/Product_Docs/UBX-G7020_ProductSummary_(GPS.G7-HW-10001).pdf, 2014.

[18] W. Fraczek, "Mean sea level, gps, and the geoid," http://www.esri.com/news/arcuser/0703/geoid1of3.html, 2003.

[19] W. Torge, *Geodesy*. de Gruyter, 2001.