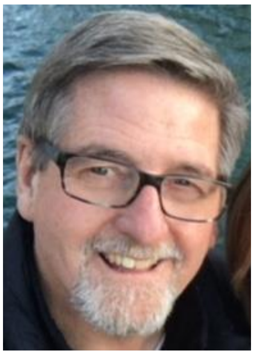
TRUCKS THAT REFUSE TO CRASH: NEW OBJECTIVES FOR SELF-DRIVING VEHICLES
THE ROLE OF ARTIFICIAL INTELLIGENCE



J.H. WOODROOFFE
Woodrooffe
Dynamics Ltd
Research Scientist
Emeritus University
of Michigan.

Abstract
This paper proposes altering the focus for developing self-driving vehicles from the goal of replacing the human as the vehicle pilot to creating vehicles that refuse to crash while the human is driving, and then eventually graduating to self-driving vehicles.

By taking this approach, it is expected that safety improvements would occur earlier and that as the self-driving sensing, processing, artificial intelligence and control systems mature, the role of the human can be reduced and eventually made redundant. The paper argues that artificial intelligence (AI) will play a significant role in crash avoidance of future vehicles and that developing a crash refusal strategy will help in AI development to maximize safety outcome. To advance this argument, two increasingly common crash avoidance technologies are studied exploring the proportion of crashes that these technologies cannot address unless artificial intelligence is at play.

Keywords: Heavy vehicles, trucks, safety, self-driving vehicles, crash avoidance, artificial intelligence.

1. Introduction

There is great enthusiasm for the concept self-driving vehicles which has permeated government institutions paving the way for an idea that has yet to prove its merit or viability at scale. The influential US House Energy and Commerce Committee recently passed the "Self Drive Act" (1) by a vote of 54 to 0. The intent of the legislation among other things is to amend title 49, United States Code to provide special allowances for such vehicles. The legislation allows manufacturers sell up to 25,000 automated cars a year without meeting all federal safety standards, and up to 100,000 cars after three years. According to the New York Times Editorial Board, the pending legislation would speed the deployment of self-driving cars without human controls and bar states from blocking autonomous vehicles (2).

This paper takes a critical look at the challenges facing the creation of high-level self-driving vehicles and argues that the focus on creating driverless vehicles may not be the best way to reduce road fatalities. By changing the focus to developing vehicles that refuse to crash while maintaining the human as the primary vehicle controller, it is postulated that safety benefits of crash avoidance would be realized earlier. The concept of maintaining human involvement in the driving task is very much how the traditional vehicle manufacturers are approaching the introduction of automated control. However non-traditional vehicle manufacturers specializing exclusively in driverless vehicles appear to be much more aggressive arguably introducing greater overall safety risk by rushing developing technology into such a complex and unpredictable road environment.

2. Understanding the challenge of self-driving vehicles

It is often stated that because almost all traffic crashes are the result of human error, it would be relatively easy for automated vehicles to outperform humans in the driving task. If for example, 95 percent of fatalities were the result of human error then automated vehicles should be able to sharply reduce vehicle fatalities by removing the human from vehicle control.

Such arguments fail to consider that serious traffic crashes are rare events and that humans are, in general, highly successful at preventing crashes. In the US, vehicle related fatalities occur at a rate of approximately 0.73 fatalities per 100 million vehicle km traveled (3). The average annual distance travelled per US vehicle is about 19,000 km. Based on the average distance travelled per year and the fatal crash rate, it would take an average of about 7,210 years of single vehicle travel for a fatal crash to occur. Put in another way, the probability of a fatality per vehicle for a given year is 1 in 7,210 or about 0.014 percent. Looking at the reciprocal, at the single vehicle level with humans in control, chances are the vehicle will be 99.99 percent fatality free for a given year.

With this in mind, the task of creating successful self-driving vehicles can be divided into two parts;

1) reducing the crashes caused by human error,
2) faithfully replicating what the human successfully does at avoiding crashes.

There is no doubt that self-driving vehicles will reduce crashes that are currently caused by human error, but the much greater challenge will be to faithfully replicate the fatality free driving success that humans currently have. This concept is modeled in Figure 1 showing that high-level self-driving systems would need to replicate what humans are doing successfully, without fail, and in addition significantly reduce crashes that are on the tail of the driving task distribution curve. The horizontal axis represents increasing risky encounters and the vertical axis represents the driving population.

Viewed from this perspective the magnitude of the challenge becomes clearer. It shows that the task of developing high level self-driving vehicles at scale will be complex and, in some ways, unprecedented in terms of engineering, control and artificial intelligence content.

All indications are that the present level of artificial intelligence sophistication is nowhere near what is needed to fulfill the requirements of high-level driverless vehicles for fatality free driving success.

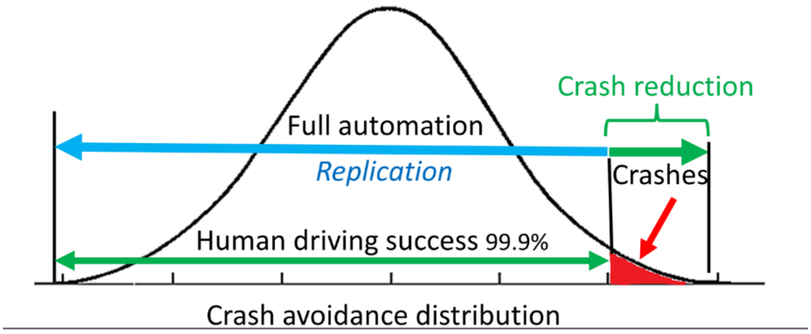


Figure 1 – Representation of the challenge of developing technology that can improve on human crash avoidance.

2. Artificial intelligence for driverless vehicles

Artificial intelligence (AI) is in the early stages of development. Where systems are simple, and reasonably constant, current AI works well. But much of the driving environment is steeped in nuance which is very challenging for AI to decipher. For example, AI has problems understanding sarcasm in speech or written text. It tends to interpret phrases literally. Computer scientist Pedro Domingos make the point that “people worry that computers will get too smart and take over the world, but the real problem is that they’re too stupid and they’ve already taken over the world” (4).

“Artificial intelligence presents a cultural shift as much as a technical one. This is similar to technological inflection points of the past, such as the introduction of the printing press or the railways. Autonomous systems are changing workplaces, streets, and schools. We need to ensure that those changes are beneficial, before they are built further into the infrastructure of every-day life” (5). The Crawford article questions how safe driverless vehicles should be before they are allowed to freely operate, and what tools should be used to determine their worth and effectiveness.

To better understand the roll of artificial intelligence in crash reduction, this paper will focus on two crash avoidance technologies that have been developed and marketed for larger trucks. Their effectiveness has been estimated by crash type and scaled to the national level under contract to NHTSA (6, 7). These studies were rigorous enough to provide an understanding of when these systems are successful on their own and when they are not successful. In this paper we hypothesize that in cases where the technology is currently unable to prevent a crash, the addition of future AI would provide the necessary input to avoid the crash. The goal is to provide an example of how significant AI input is likely to be in successful high level driverless vehicle systems.

The existing systems considered in this paper are electronic stability control and forward collision mitigation and braking which are relatively recent innovations in truck safety.

1. Electronic stability control works in the background and will automatically de-throttle the engine, and initiate braking without driver involvement when the system detects loss of control or vehicle over-speed in a curve. The technologies have simple algorithms that estimate center of mass height and adjusts vehicle speed in curves accordingly.

2. Forward Collision Avoidance and Mitigation systems use the same sensors and control systems as adaptive cruise control. These systems are packaged together. Forward collision control and braking operates in the background. When a potential forward collision is identified, the technology warns the driver. If the condition persists and a collision is imminent, the system will apply the foundation brakes to reduce the impact speed or stop the vehicle prior to collision.

Knowing the types of crashes that these technologies can address and knowing the efficacy of the technologies in terms of fatalities prevented, it is postulated that the remaining fatalities in these crash categories would require higher level intervention likely guided by artificial intelligence to prevent fatalities.

3. The efficacy of the crash avoidance technologies

To explore this hypothesis, truck crash data are examined to determine which crash types would be avoided through simple technology application and which crash types would require significant artificial intelligence content to avoid crashes.

3.1 Electronic Stability Control

To assess the effectiveness of electronic stability control independent crash datasets using engineering and statistical techniques were analyzed to estimate the probable safety benefits of ECS for 5-axle tractor-semitrailer vehicles. The conventional approach for assessing the safety benefits of vehicle technologies is to analyze crash datasets containing data on the safety performance of vehicles equipped with the technology of interest. Because the deployment of the stability technologies for large trucks was in its infancy at the time of this study, national crash databases did not yet have a sufficient amount of factual data that could be directly linked to the performance of the technology. Therefore, a novel method of examining the potential benefits of ESC was used. Crash scenarios that could likely benefit from the technologies were selected from national crash databases and the probable effectiveness of each technology was estimated. The analysis in this study did not have the advantage of examining representative crash datasets that contain identifiable data from vehicles equipped with the technology. Therefore, the analysis was based on probable outcome estimates derived from hardware-in-the-loop simulation, field test experience, expert panel assessment, and fleet crash data and these methods were used to estimate the safety benefits from the national crash data population

The crash scenarios selected that could potentially be addressed by ESC are as follows:

1. Rollover from untripped rollover
2. Rollover from first harmful event
3. All other rollovers
4. Loss of control from accident type
5. Loss of control from critical event
6. Loss of control from first event jackknife
7. Loss of control from instability prior to the crash
8. Loss of control from single vehicle run-off-the-road where the driver made an avoidance maneuver

Each of these scenarios were analyzed and from this study population, cases where ESC would have prevented crashes fatalities and injuries were identified. Table 1 contains data representing the results of the study (6). The adjusted annual study population contains crashes from the scenarios listed above and corresponding estimates of crashes that could be prevented by ESC. The difference between the prevented crashes, deaths and injury categories and the corresponding study population are considered as potential opportunities for artificial intelligence to play a role in crash mitigation or avoidance. With this approach it is estimated that for crash scenarios associated with ESC functionality, 58 percent of crashes, 51 percent of deaths and 71 percent of injuries cannot be prevented by ESC alone and therefore could benefit by artificial intelligence input.

Table 1 – Adjusted Annual Study Population Crashes, Deaths, and Injuries, and Estimated Crashes, Deaths, and Injuries Prevented by ESC

	Annual total study population	Prevented by	Potentially preventable (counts)	Potentially preventable (percent)
		ESC	Using Artificial intelligence	
Crashes	11,224	4,659	6,565	58%
Deaths	255	126	129	51%
Injuries	14,233	5,909	8,324	71%

3.2 Forward Collision Avoidance and Mitigation (F-CAM) system

The study used for this paper was conducted by the University of Michigan Transportation Research Institute (UMTRI) under a Cooperative Agreement between NHTSA and Meritor WABCO (7,8). The objective of the study was to estimate the safety benefits of Forward Collision Mitigation Systems that include Forward Collision Warning with Collision Mitigation Braking technology as applied to heavy trucks, including single unit and tractor semitrailers.

The study method is summarized as follows:

(1) first characterize the actual performance of these systems in various pre-crash scenarios under controlled test track conditions, and then reverse engineer the algorithms that control warnings and automatic braking actions;

(2) developing a comprehensive set of simulated crash events representative of actual truck striking rear-end crashes. This virtual, “reference” crash database was developed by analyzing vehicle interactions (or conflicts) from naturalistic studies to create thousands of crashes in a computer simulation environment, and then weighting each simulated crash based on probabilities derived from crash databases;
(3) overlaying (or inserting) the technology algorithms into the simulations of each crash event and observe the kinematic impacts (i.e., benefits) from having initiated warnings and/or automatic braking (including reduction in impact speed, or crash elimination of the crash).

The crash population that could likely benefit from the technologies was identified using nationally representative crash databases. The results from the simulation studies were applied to the national crash population.

The study focused exclusively on truck-striking rear-end crashes using five crash threat scenarios. These scenarios were used in both simulations and full-scale track testing and are defined as follows:

<u>Lead vehicle decelerating</u>
The initial conditions in this scenario are the truck and the lead vehicle traveling in the same direction, at the same speed, at a predetermined range, and in the same lane. The conflict occurs when the lead vehicle driver slows at a nominally steady-state rate to either a slower speed or to a stop.

<u>Closure from long range</u>
This scenario characterizes the system response when the truck approaches a slower moving lead vehicle from behind in the center of the same lane. In this condition the truck and lead vehicle are traveling at constant speeds.

<u>Lane change cut-in/out</u>
This scenario is designed to test the system’s response to a slower moving target vehicle that “suddenly appears” in the truck radar at short range. In the Cut-in scenario, the lead vehicle makes a lane change in front of a faster moving truck. For these tests, the target initial range between the truck and lead vehicle was 30 m.

The Cut-out scenario involves a third vehicle. In this scenario the truck follows vehicle 1 at the same speed at a fixed following distance. Both the truck and vehicle 1 approach a slower moving vehicle 2. The conflict is created when the driver of vehicle 1 a sudden lane change to reveal vehicle 2.

<u>Stopped vehicle</u>
In this case, the lead vehicle travelling in the same direction as the truck stops in the center of the same lane after the truck radar has engaged the vehicle. In this condition the system identifies the vehicle as a moving target and will react when the vehicle stops.

<u>Fixed Vehicle</u>
This case is like the stopped vehicle scenario except it the target vehicle has already stoped in the center of the same lane before the truck radar has engaged the vehicle. In this condition the system disregards the vehicle will not react. It is part of the radar algorithm that disregards stationary objects such as road signs and overpass bridges.

Based on these scenarios Forward Collision Avoidance and Mitigation (F-CAM) system benefits were categorized by crashes avoided and crashes mitigated. The most significant research challenge was the estimation of benefits in mitigated crashes. This task required the development of new technical methods based on distribution modeling which used a combination of naturalistic driving data, existing crash data, and human factor brake performance data.

As shown in Tables 2, and 3, for tractor semitrailers in the US, there are approximately 16,000 rear-end truck striking crashes each year, with about 192 fatal and 5,000 injury crashes. These truck-striking rear-end crashes result in approximately 231 fatalities and about 8,000 total injuries.

Table 2 – Estimated Annual Rear-end Striking Crashes, Tractor-Semitrailers,

Crash type	Fatal	Injury	PDO	Total
	N	N	N	N
LV fixed	62	882	2,119	3,078
LV stopped	13	1,244	2,987	4,263
LV slower	90	1,199	1,794	3,082
LV decel.	18	1,502	3,152	4,750
LV cut-in	9	156	649	814
Total	**192**	**4,983**	**10,701**	**15,987***

"PDO" specifies property damage only crashes.
* Total includes 111 crashes of unknown injury severity.

Table 3 – Fatalities and Injuries in Rear-end Striking Crashes, Tractor-Semitrailers,

Crash type	Injury severity				Total injuries
	Fatal	A-injury	B-injury	C-injury	
LV fixed	78	139	335	861	1,413
LV stopped	16	158	431	1,179	1,782
LV slower	107	601	865	727	2,300
LV decelerating	22	303	605	1,251	2,180
LV cut-in	9	87	48	115	259
Total	**231**	**1,287**	**2,284**	**4,132**	**7,934**

For the annual US injury severity population that F-CAM could target shown in Figure 3, the analysis found the F-CAM technology would reduce fatalities by 44 percent, injury severity by 47 percent and property damage only crashes by 20 percent as shown in Table 4.

Table 4 – Reduction in Injury Severity by F-CAM System for Tractor Semitrailers

Device	Fatal	Injury	PDO
F-CAM	44%	47%	20%

From these findings we deduce that for the F-CAM scenarios examined, artificial intelligence has the potential to influence the outcome of 56 percent of fatalities, 53 percent of injuries and 80 percent of property damage only crashes. Table 5 shows the potential of artificial intelligence for crash scenarios related to ESC and F-CAM when combined with these technologies. Since the technologies alone address less than 50 percent of cases, the potential for artificial intelligence to provide improvements in safety is evident in most of cases.

Table 5 – Potentially preventable percent of fatalities and injuries by artificial intelligence when combined with ESC and F-Cam technology

	Potentially preventable Using Artificial intelligence	
	ESC	F-CAM
Deaths	51%	56%
Injuries	71%	53%

4. Conclusions and discussion

This paper discusses the challenges facing the development of reliably safe high level self-driving vehicles. It found that human vehicle controllers (drivers) are about 99.9 percent successful at avoiding fatal crashes and shows that one of the greatest challenges of self-driving vehicles will be to replicate the current success of human drivers.

Through the examination of the efficacy of two crash avoidance technologies, it was found that the ESC and F-CAM alone addressed less than 50 percent of crashes injuries and fatalities in scenarios that were identified as being applicable to the technologies. It is concluded that artificial intelligence has the potential to address most of the cases that could not be managed by the existing technology alone.

While self-driving vehicles are anticipated, focusing on human controlled vehicles with systems that prevent crashes may be a more practical development strategy. Such an approach will likely bring better safety benefits sooner, prove the reliability of technology, control logic and artificial intelligence than if the exclusive focus were to develop self-driving vehicles.

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