Performance Comparison of Forward Collision Warning Algorithms

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***Abstract*—Forward Collision Warning Systems (FCWs) are an integral part of Cooperative Vehicle Safety (CVS). FCWs alert the driver of a possible collision scenario with the leading vehicle and thus allow the following vehicle to escape a life-threatening situation. Presence of these algorithms in CVS has shown to significantly reduce the number of collisions. However, it is also true that not all of these algorithms are sophisticated enough to perform accurately under all possible circumstances and are limited by certain assumptions.**

This paper considers three common FCWs, i.e. CAMP linear, knipling and NHTSA. We attempt to compare the performances of knipling and NHTSA algorithms in terms of the number of warnings they generate and the accuracy of those warnings. We also analyze the time-shift of the warnings generated by the two algorithms. We use CAMP linear as the ground-truth for all of the calculations.

***Index Terms*—Intelligent Transport Systems; Vehicular Networks; FCW; Driver Assistant.**

I. Introduction

An introductory step in Cooperative Vehicle Safety (CVS) is to include a mechanism in every vehicle that can avoid a hazardous situation by alerting the driver. Forward collision warning systems (FCWs) are useful in this case since they can utilize modern sensing and communication technologies such as DSRC and CV2X in order to generate warnings for the driver. FCW algorithms are being used in many high-end vehicles for collision avoidance and the warnings generated by these algorithms have significantly reduced the number of crash scenarios [1]. There are numerous FCW algorithms available in the modern era that consider position, velocity and/or acceleration of leading vehicle (LV) and following vehicle (FL) and decide whether there is a need to generate a warning for the driver.

Although any FCW algorithm can avoid a certain number of collisions, it is essential to choose the best algorithm that covers all the possible near-crash scenarios. This paper considers three common algorithms i.e., CAMP linear, knipling and NHTSA. We use CAMP linear as ground truth and carry out a series of experiments to compare the performance of knipling and NHTSA. We focus on the number of warnings generated, the length of the warning ranges and the accuracy of generated warnings in order to find out the better algorithm.

II. Related Work

An extensive amount of work has been done in the area of FCW algorithms. The study in [1] proposes a simulation framework for CVS where it contains a driver model and allows analysis of human reaction (braking) to a warning. It first tests the framework without any FCW and then tries each of CAMP linear, CAMP logistic, knipling, NHTSA imminent, NHTSA intermediate and NHTSA early algorithms. The paper shows that all these algorithms assist in avoiding crash scenarios. In particular, it points out that on average, NHTSA performs better than knipling and CAMP linear. [2] is the Department of Transport (DOT) report that provides an vast analysis on CAMP linear, knipling and NHTSA. It provides equations for the implementation of these algorithms and explains the assumptions outlining each of them. The research in [3] also provides an insight into these three algorithms and outlines the strengths and weaknesses of these algorithms.

III. Proposed Approach

In this work, we are using data from virginia tech database and simulated car following model. We are provided with trajectories of two vehicles: LV and FV. This database comprises of around 800 scenarios representing crash and near-crash scenarios. Due to time constraints, we use 100 scenarios for our calculations. We can assume that the information related to LV is provided to FV through cooperation (DSRC or CV2X). This information is passed to the three algorithms mentioned above and they run their respective crash detection schemes to decide whether they need to warn the driver in the FV about a potential crash or near-crash scenario.

This study considers CAMP linear as the ground truth for all the calculations. The approach of this algorithm is to isolate kinematic conditions such as velocity and acceleration of the FV and LV that entail what would be characterized as 'hard' imminent brake or a 'normal' imminent brake for an active and alert driver. The three types of scenarios considered in this algorithm are: LV-stationary, LV-braking, and constant relative speed between FV and LV.

Knipling algorithm is the simplest algorithm of the three that describes two straightforward equations that are implemented as a possible head-way warning algorithm. The two equations refer to lead-vehicle stationary (LVS) scenario or a lead-vehicle moving (LVM) scenario. Since it is a very simple algorithm, it is shown in [1] to produce the least number of warnings and prevent the minimal number of crash or near-crash scenarios.

NHTSA (National Highway Traffic Safety Administration) algorithm is the most sophisticated out of the three algorithms studied in this paper. The two unique aspects of this algorithm are the induction of driver warning sensitivity (near, middle and far) and three-stage warning alert system (early, intermediate and imminent warning). The algorithm is divided into three main parts where the first part is to calculate the stopping time of LV and FV depending on one of the three alert levels. The second part is to calculate the distance-to-miss (Dmiss) based on the stop times calculated above. Finally, if the Dmiss is less than a threshold (Dthresh), then the appropriate alert is generated for the driver in the FV. NHTSA has been shown in [1] to have the highest frequency of warning generations and prevent the most number of crash and near-crash scenarios.

IV. Experimental Results

In order to compare the three algorithms, we first plot the mean number of warnings against PER for each algorithm in figure 1. As we can observe from the plot, NHTSA generates more warnings than both knipling and CAMP linear. It can be noticed that the number of warnings increase for NHTSA-imminent and NHTSA-early as PER rises. As compared to NHTSA, CAMP linear and knipling both have lesser number of warnings. Knipling does the worst because it only considers two scenarios of LV being stationary or moving, thereby producing the least number of warnings.

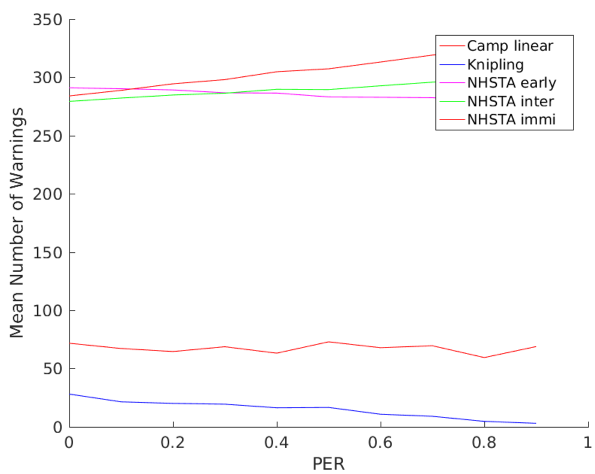

Fig. 1. Mean number of warnings vs. PER

Although figure 1 provides a good understanding of the average number of warnings generated for each value of PER, it is not enough to measure the reliability of any algorithm. In addition to the warning generation, the time-shift in warnings as compared to the ground truth is more significant than just the number of warnings. We choose a specific value of PER (30%) and a vehicle mobility scenario and plot the warning range (Rw) against time of CAMP linear and knipling in figure 2. We separately plot the distance-to-miss values of NHTSA in figure 3 because NHTSA doesn't provide a Rw.

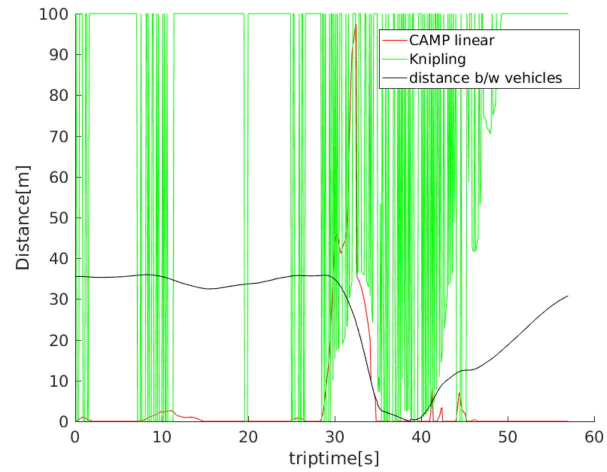

Fig. 2. Warning Range vs. Triptime

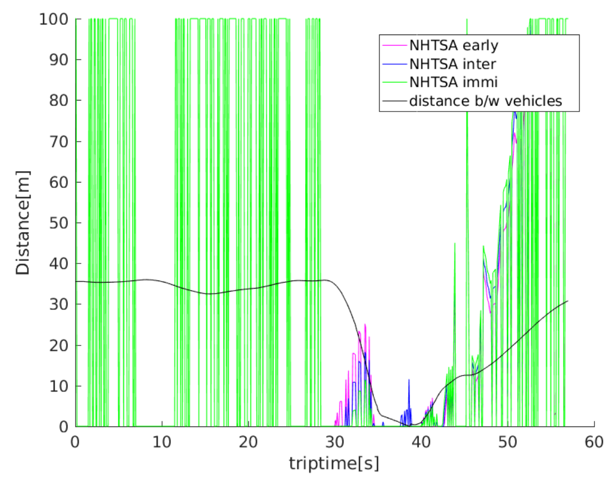

Fig. 3. NHTSA Distance-to-Miss vs. Triptime

The red plot in figure 2 represents the Rw of CAMP linear. The green plot represents the Rw of knipling and it can be seen that it consists of a lot of noise and variations throughout the triptime. This can be because of the PER as well as the fact that it is a comparatively weaker algorithm as mentioned earlier. Despite that, it can be pointed that it follows the general pattern of CAMP linear. The Rw of knipling tends to be close to that of CAMP linear especially during the trip time of 30s to 40s. This is the distance where in this scenario, the distance between LV and FV, which is shown by the black plot, falls. This causes CAMP linear to increase its Rw and although the Rw of knipling is continuously varying, it is still able to follow the pattern of CAMP linear.

We couldn't plot NHTSA on figure 2 because there is no notion of Rw in this algorithm. Instead, it returns a Dmiss that basically implies the distance by which the FV would miss the collision with LV. Thus we plot it separately on figure 3 along with the distance between the two vehicles. The plots for NHTSA early, intermediate and imminent all show a similar trend. The most significant observation from this plot is that as the distance between the two vehicles reduce, the Dmiss of all the three NHTSA plots reduces. This proves the accuracy and reliability of the algorithm since the algorithm is able to detect the fall in distance between vehicles and reduce its Dmiss. This raises the probability of the Dmiss being lower than the Dthresh which generates more warnings and alerts the FV of a possible collision.

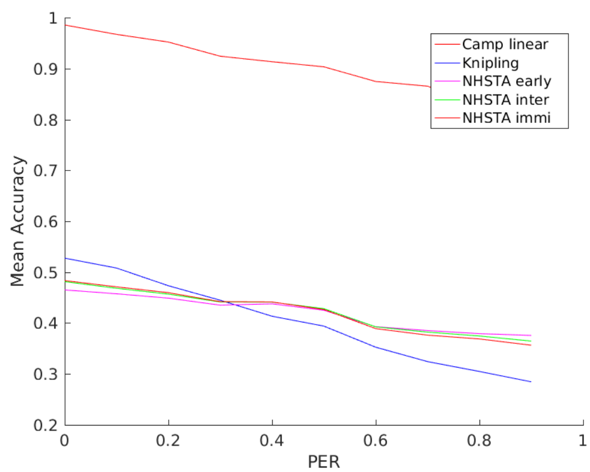

Fig. 4. Mean Accuracy vs. PER

Next we plot the mean accuracy against PER for all the algorithms as shown in figure 4. As we can observe, the accuracy of CAMP linear is really high even at a PER of 0.9. This is because we are basically comparing CAMP linear at different PERs with CAMP linear itself with no error. By observing the plot of knipling, it can be seen that it has a very low accuracy as compared to CAMP linear. Surprisingly, NHTSA accuracy plots for early, intermediate and imminent warnings are also lower than that for CAMP linear. This behavior is surprising because NHTSA is known to be more sophisticated and accurate than both CAMP linear and knipling. One possible reason for that might be that since we are taking CAMP linear as ground truth and in reality even CAMP linear can make wrong predictions of warning generation, so there might be cases where NHTSA is actually predicting a correct warning but CAMP linear is not and since we are considering CAMP linear as the ground truth, we are taking those warnings of NHTSA as incorrect. As a result, the accuracy of NHTSA is shown be lesser than that of CAMP linear. One major observation from figure 4 is that as PER increases, knipling has a steeper fall as compared to NHTSA although they both have similar accuracy for ideal scenarios (PER=0). This shows that NHTSA performs better than knipling under high PER which is more common in real-world traffic scenarios.

Since the accuracy plot doesn't provide enough information about the performance of knipling and NHTSA, we attempt to analyze the precision of these algorithms against CAMP linear in figure 5. It can be seen that NHTSA has a slightly better precision than knipling. One thing to notice is how the precision of CAMP linear has a steep drop as the PER increases. The precision of CAMP linear goes from around 1 to 0.6 as PER increases from 0 to 90%. This shows that a higher loss has a big impact on the performance of CAMP linear.

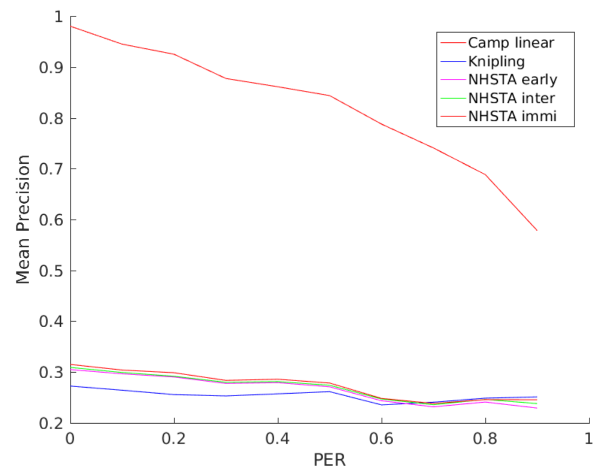

Fig. 5. Mean Precision vs. PER

All the previous plots shown in the paper have been the result of using a constant speed model (CSM). In order to guarantee the reliability of a FCW algorithm, it is critical that it should perform reasonably well under other models as well and not just favor one particular model. Therefore, we now shift our focus towards a constant acceleration model (CAM) and show plots for accuracy, precision and number of warnings in figure 6, figure 7 and figure 8 respectively.

Both in figure 6 and figure 7, the respective accuracy and precision of both knipling and NHTSA are mostly constant with minuscule variations. On the other hand, the accuracy and precision of CAMP linear falls as PER increases. This shows that CAMP linear is sensitive to both CSM and CAM and a more reliable algorithm. The performance of the other two algorithms imply their accuracy is dependent on the inclusion of a constant speed model. This also explains why CAMP linear was a good choice for the ground truth algorithm for all scenarios.

The next plot in figure 8 compares the number of warnings against PER of all the algorithms for a CAM. It shows that changing from CSM to CAM doesn't cause a major difference in the number of warning generated by knipling and CAMP linear. However, for NHTSA, the plots become more stagnant as opposed to those in CSM. The plots from figure 8 imply that changing the model doesn't necessarily change the average number of warnings however, the accuracy of those warnings is affected as can be seen in figure 6.

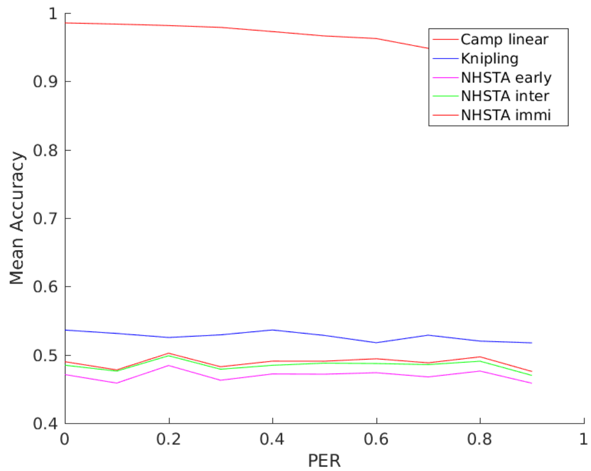

Fig. 6. Mean Accuracy vs. PER - CAM

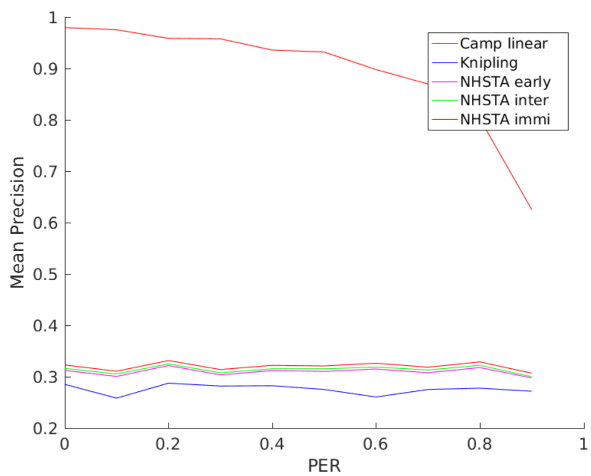

Fig. 7. Mean Precision vs. PER - CAM

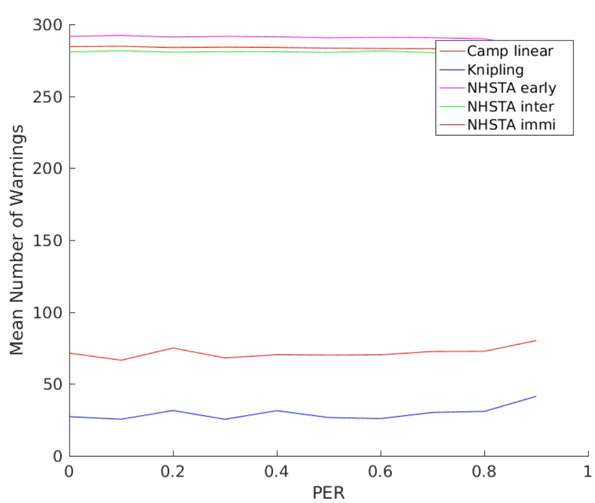

Fig. 8. Mean Number of Warnings vs. PER - CAM

V. Improvements

There can be multiple improvements to the current code implementing all these algorithms and plots. The first improvement can be to study the effect of transmission rate on the accuracy, precision and the number of warning generated. For this study, a constant transmission rate of 10Hz was used while the PER was changed from 0-90%. A change in transmission can also greatly impact the performance of a FCW algorithm.

Secondly, all the NHTSA calculations done in this paper assume the driver sensitivity of 'near' which implies a careless driver. Performance of NHTSA can be further evaluated by considering the other two driver sensitivities, namely 'middle' and 'far'. This will reflect how the algorithm performs for three main kinds of driver behaviors.

Thirdly, we should choose a better algorithm to be the ground truth than CAMP linear. Looking back at figure 2 for the Rw plot of CAMP linear, we can observe that upon a decrease in the distance between FV and LV, the Rw initially increases however, soon it starts to fall even though the distance between the vehicles is still falling. This proves that CAMP linear is not fully accurate and reliable. Keeping CAMP linear as the ground truth has affected the results of NHTSA throughout this study as well.

Lastly, as in [1], a driver model should be included in this study that takes the warnings generated by the three algorithms as input and tries to avoid a collision. That would provide a more sophisticated performance analysis of the algorithms.

VI. Conclusion

This paper attempts to provide a comparison between two common algorithms, i.e., knipling and NHTSA. It is important to set a ground truth for any comparison and for this purpose we use CAMP linear. We observed that both knipling and NHTSA try to react to a near-crash or a crash scenario, however NHTSA performs slightly better. As PER rises, the accuracy of knipling gets worse than NHTSA since it generates the least number of warnings and has a higher time-shift in warnings as opposed to NHTSA. NHTSA produces the most number of warnings, has higher accuracy and lesser time-shift in warning generation. We discussed possible improvements to the algorithms and an inclusion of a driver model to fully utilize the generated warnings and check if they assist in avoiding a collision.

References

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