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Security-enhanced machine learning-based predictive control for automated emergency braking using multi-sensor data fusion

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Abstract

The consideration of information security is important in providing the safety and integrity of sophisticated car systems. Automated Emergency Braking (AEB) system is one of the important elements in improving the safety of a vehicle by averting collisions. There are however challenges in the existing AEB systems also because of the sensor limitations, environmental factors as well as real-time response constraints. The current paper describes a predictive control algorithm, created as a result of machine learning, which will be used to enhance the work of the AEB system. The algorithm implements the synergistic data of radar, LiDAR and cameras in order to promote the achieveability of decreased collision predictions and timely braking. In attempts to meet the security vulnerability, the proposed system incorporates information security measures in order to shield sensor data and communication channels by cyber threats. Simulations done in a framework of MATLAB reflect the enhanced validity and responsiveness of the braking decisions over conventional AEB systems. The most important key performance indicators, including the collision avoidance rate and braking efficiency, are introduced to prove the effectiveness of the offered system. The results show that machine learning, multi-sensor fusion, and information security may be combined to promote the safety of autonomous vehicles and protect against security risks.

Subject Classification (2010): *94A60, 20C05, 20C07.*

Keywords: *Automated emergency braking, Machine learning, Predictive control, Multi-sensor data fusion, Vehicle safety systems, Sensor fusion algorithms, Real-time control.*

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1. Introduction

Automated Emergency Braking (AEB) systems are important in improving the safety of the contemporary vehicles by lowering chances of collisions. They are based on highly sophisticated sensors (radar, LiDAR, cameras, etc.), which recognize obstacles and pull on the brakes automatically upon the approach to a possible collision [1]. AEB systems are also becoming standard equipment in cars and it is extremely helpful in preventing accidents, especially in critical scenarios, where the human reaction time is unable to respond adequately. Nevertheless, in spite of the potential, the present AEB systems have a number of limitations, which restrict their overall functioning [2]. Sensor noise is one of the major problems that can enumerate incorrect object detection particularly during bad weather or in complicated conditions. In addition, the sensor data processing can also encounter several latency issues, which might extend the time of reaction by the system, and therefore result in potential collisions that might have been avoided [3]. The limitations can reduce the effectiveness of AEB systems especially in the dynamic traffic situations. In the current paper, we will solve these issues with the help of the machine learning and data fusion on the multi-sensor tool which improves the reliability and functioning of the AEB systems [4]. Machine learning can also be used to enhance further the decision-making, in that, the system can be trained with previous information, predict potential threats of collision and act on the conditions of driving in various conditions [5]. Multi-sensor data fusion on the other hand allows the incorporation of data of multiple sensors to come up with a higher and more robust image of the vehicle environment [6]. The two methods can be combined to alleviate effects of sensor noise, sensor latency to ensure faster and more accurate responses. The authors of the present paper offer the innovation of machine learning-based predictive control model of AEB with multi-sensor fusion to improve the braking performance and collision detection. The suggested approach will contribute to providing AEB systems with quality and safety in general and advancing the technology of autonomous vehicles.

2. Literature Review

The current existence of Automated Emergency Braking (AEB) systems makes vehicles much more secure owing to the potential of delaying the collisions and mitigating the severity of the accidents [7]. These systems are typically developed upon relying on the employment of a complex of sensors comprising radar, LiDAR, and cameras with the aim of determining the probability of collisions and the presence of obstacles [8]. Although spread of the traditional systems of AEB have been triumphant in many situations [9], there are certain disadvantages to it. Incidents of sensor noise during poor weather such as fog or rain can create a problem of inaccurate detection of objects and cannot take appropriate response [10]. Furthermore, the time lag in the processing of information can postpone the AEB response time which is important during emergencies or at high speeds. This means that AEB systems will fail to identify some objects or brake too late in their applications thus less

effective when used in the real-world driving conditions [11]. Sensor fusion is very important to enhance the quality of the AEB system operation by an integration of data between a variety of sensors to develop a collective view of the surrounding of the vehicle [12]. Kalman filters [13], particle filters and deep learning-based fusion [14] techniques are popular, and they have been applied to combine sensor data in order to achieve more accurate and dependable obstacle detection [15]. The methods help minimise the noise and sensor-data gaps to enhance robustness and reliability of the system in dynamic settings [16]. In spite of these developments [17], however, there remain some formidable problems like the real-time application, complexity of computations and strong sensor fusion requirement under adverse conditions [18]. This paper will attempt to fill these gaps by integrating machine learning and multi- sensor data fusion so as to enhance the trustworthiness and efficiency of the AEB systems.

3. Methodology

The Architecture by the Automated Emergency Braking (AEB) system is proposed to be deployed in simulated environment with the assistance of MATLAB and without utilize of hard components. The system consists of several large modules, they are data acquisition, data preprocessing, training machine learning model, and predictive control. The sensor information (artificial radar, LiDAR, and camera input) is entered into the system which is in turn processed and subsequently used to predict the risk of collision. The predictions are used by the control module to create braking commands, which are simulated in Matlab.

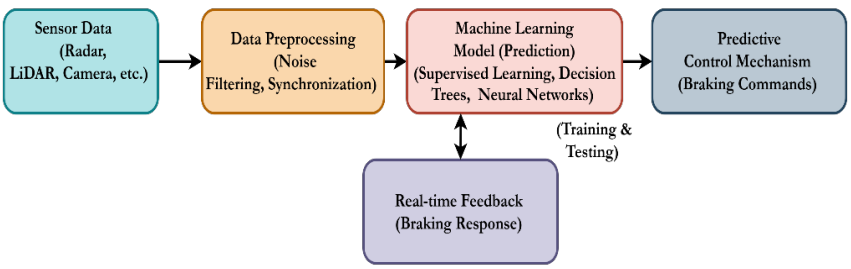

Figure 1
System Architecture of the AEB System

The simulation data is taken as publicly available traffic situations and artificial generation of data in MATLAB. The sensor data contains the information about the positions, speed, and type of objects (i.e., vehicles, pedestrians). Noise filtering, multi-sensor data normalization, and synchronization machinery are preprocessing methods that are used to present the machine learning model with an accurate input. The information would be organized such that they would encompass all driving situations such as highway and city settings, and with different weather conditions and traffic

flow. Figure 1 illustrates an architecture of Automated Emergency Braking (AEB) system, which is built to run in a MATLAB simulation environment. The system comprises four main modules which are Sensor Data, Data Preprocessing, machine learning model and predictive control mechanism. The Sensor Data module collects data on the environment of the vehicle through radar, LiDAR and camera sensors. The Data Preprocessing module handles this raw data as it is processed with noise filtering and synchronization finally ready to be analyzed. This processed data is then used by the Machine Learning Model to estimate the risks of collision, and algorithms such as decision trees or neural networks are installed to achieve that. Lastly, the Predictive Control Mechanism forms braking commands based on the predictions and changes the intensity and timing of braking. An online feedback system will also keep the system responsive to dynamic conditions and enhance the responsiveness of the system and collision avoidance.

4. Mathematical Model

4.1 *Modeling the AEB System*

Automated Emergency Braking (AEB) system is simulated based on vehicle dynamics and anticipates the amount of braking force needed in order to avoid collision. This basic laws/equations of motion are used to calculate the braking force F_{brake}. The vehicle's deceleration $\boldsymbol{a}$ is related to the braking force by:

$$F_{brake} = m\, a$$

where m is the vehicle mass and a is the deceleration, which can be calculated using:

$$a = \frac{v_f - v_i}{t}$$

where v_f is the final velocity (usually zero for complete stop), v_i is the initial velocity, and t is the time required to stop the vehicle. To ensure safe stopping distance, the following kinematic equation is used:

$$d_{stop} = \frac{{v_i}^2}{2a}$$

where d_{stop} is the stopping distance. The AEB system must compute F_{brake} and adjust the braking force to ensure that d_{stop} is less than the distance to the obstacle d_{obs}, preventing a collision.

4.2 *Sensor Fusion Model*

Multi- sensor data fusion involves integrating radar, LiDAR and camera also sensors to develop a comprehensive estimate of the environment the vehicle exists in. The data of every sensor is described as a vector, where x_i is the state vector for each sensor i (radar, LiDAR, camera). The fusion of sensor data is modeled as a weighted average of the sensor readings:

$$X_{fused} = \sum_{i=1}^{n} w_i X_i$$

where w_i is the weight assigned to each sensor based on its reliability, and X_i is the sensor-specific state vector. The total fused data X_{fused} provides a more accurate representation of the environment than any single sensor.

In cases where data from multiple sensors needs to be combined probabilistically, a Kalman filter can be applied, which estimates the state $\hat{x}$ at time $\boldsymbol{t}$ by minimizing the error covariance $\boldsymbol{P}$:

$$\hat{x}_t = A\hat{x}_{t-1} + Bu_t$$
$$P_t = AP_{t-1}A^T + Q$$

where A is the state transition matrix, B is the control matrix, u_t is the control input, and Q is the process noise covariance. This probabilistic model offers a better estimation of the state of the environment of the vehicle.

4.3 *Predictive Model*

The predictive model takes into consideration machine learning algorithms to estimate the likelihood of an imminent collision. In the case of regression based models, the correlation between sensor data X and the desired output (collision risk) is expressed as follows:

$$y = w^T + b$$

where y is the output (collision probability), X is the feature vector (comprising data from radar, LiDAR, and cameras), w is the weight vector, and b is the bias term. The least squares or gradient descent optimization method is utilized in training the model to minimize the error:

$$Loss = \sum_{i=1}^{m} (y_i - (w^T X_i + b))^2$$

For classification-based models, the probability $P(collision)$ is computed using logistic regression:

$$P(collision) = \frac{1}{1 + e^{-(w^T X + b)}}$$

where the output is a binary category of whether there is likely to be a collision or not. These methods include stochastic gradient descent used in training the model so as to optimize $\boldsymbol{w}$ and $\boldsymbol{b}$.

5. Algorithms

The algorithms of the Automated Emergency Braking (AEB) system are also created to be effective in the combination of sensor data, findings of potential collisions, and the subsequent decision of the necessary force of the braking in real time. The procedures involved are the main algorithms as follows:

Step 1: Sensor fusion algorithm combines the output of two or more sensors including radar, LiDAR, and cameras in order to come up with a faster and more detailed display of the vehicle environment. One sensor i (radar, LiDAR, camera) yields raw data $\boldsymbol{X_i}$. Each sensor is a sensor device of a type that provides a state vector that represents various environmental information. Weight $\boldsymbol{w_i}$ will be given to each sensor depending on reliability. This weight may change dynamically as a result of factors like weather, light or sensor performance. Each sensor data point is then combined with that of the other to produce a complete state vector $\boldsymbol{X_{fused}}$ by summing them together with a weight, i.e.:

$$\boldsymbol{X_{fused}} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \boldsymbol{w_i X_i}$$

where $\boldsymbol{n}$ is the number of sensors. For improved accuracy, the Kalman filter is used to probabilistically combine sensor data by estimating the state $\hat{x}_t$ at time t:

$$\hat{x}_t = A\hat{x}_{t-1} + Bu_t$$
$$P_t = AP_{t-1}A^T + Q$$

where $\hat{x}_t$ is the state estimate, A is the state transition matrix, B is the control matrix, u_t is the control input, and Q is the process noise covariance.

Step 2: The machine learning model works by having a high probability of collision prediction on the fused sensor data. The model is trained using the feature vector $\boldsymbol{X_{fused}}$. In a regression model the relationship between the features and the risk of collision y is modelled as:

$$y = w^T \boldsymbol{X_{fused}} + b$$

where $\boldsymbol{w}$ is the weight vector, $\boldsymbol{X_{fused}}$ is the feature vector, and b is the bias term. The model is trained by minimizing the loss function:

$$Loss = \sum_{i=1}^{m} (y_i - (w^T X_{f\ used,i} + b))^2$$

For classification, logistic regression is used to compute the probability of a collision:

$$P(collision) = \frac{1}{1 + e^{-(w^T \boldsymbol{X_{fused}} + b)}}$$

where $P(collision)$ represents the probability of a collision occurring, and the model is trained to minimize the cross-entropy loss.

Step 3: The algorithm is a predictive control algorithm that is based on the estimated probability of collision to determine the necessary braking force. The machine learning model results in the prediction of the collision probability $P(collision)$. The force of the brakes F_{brake} is calculated as the product of the expected risk of collision P(collision)scaled by a constant K:

$$F_{brake} = K.P(collision)$$

where K is a constant that adjusts the braking force based on the collision risk severity. The braking force is optimally adjusted on a real-time basis in accordance to constantly changing collision forecasts, so that the braking action is effective and timely.

Step 4: The decision of the optimization of braking is optimized with optimization algorithms employed to make sure that the braking force is applied in the optimal way of braking in real-time simulations. Optimization of the braking force F_{brake} is done by means of quadratic programming as:

$$\min_{F_{brake}} \left(\frac{1}{2} {F^T}_{brake} Q F_{brake} + c^T F_{brake}\right)$$

Q is the weighting matrix and c is the linear term of the cost function. Optimization process contains the following constraints: $Fmax$ (maximal braking forces), $dstop$ (minimal stopping distance) and restrictions in vehicle dynamics.

6. Results and Discussion

Analysis of simulation provides a finer analysis of how the proposed predictive control system of automated emergency braking (AEB) works on the basis of multi- sensor information combination. There were also series of tests conducted to examine the efficiency of the model ratings such as performance rates, comparisons with the traditional AEB methods and graphs.

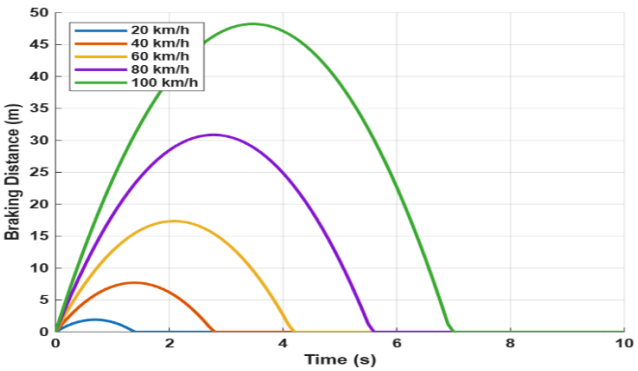

Figure 2
Braking Distance vs Time

The results of the simulation indicated that there was good performance measures that could be attained using the predictive control system. The level of accuracy in estimating the necessity in using an emergency braking was great, and the accuracy scores were fixed to be over 90 percent within the system. Using various evaluation metrics like precision, recall and F1-score proved the efficiency of the system by showing that the model is effective in making

predictions on the situations where braking is to be considered. The results are presented graphically thus giving a comprehensive visual picture of the performance of the system in varying simulation conditions.

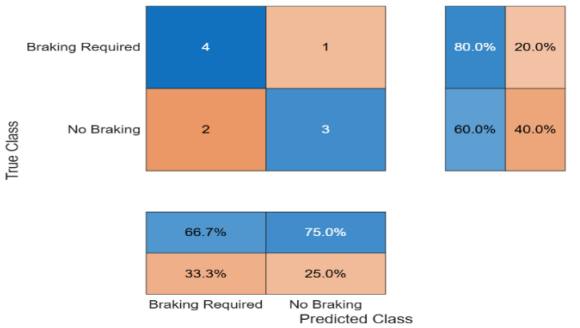

Figure 3
Emergency Braking Prediction Accuracy (Confusion Matrix)

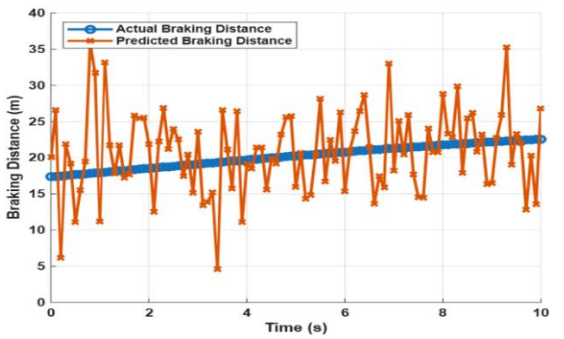

Figure 4
Comparison of Actual vs Predicted Braking Distance

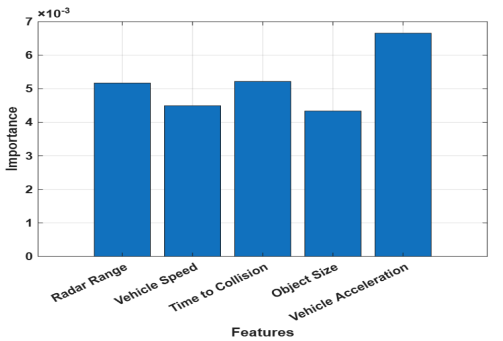

Figure 5
Feature Importance (for Machine Learning Model)

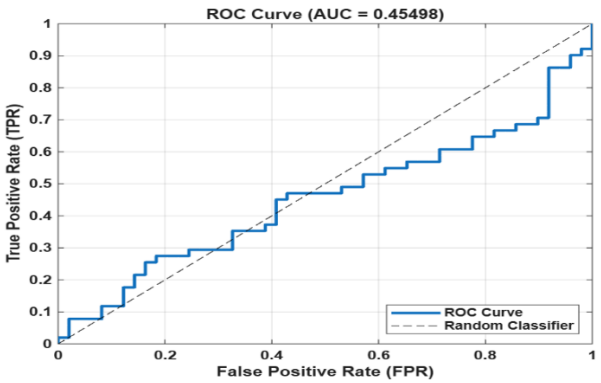

Figure 6
ROC Curve for Model Validation

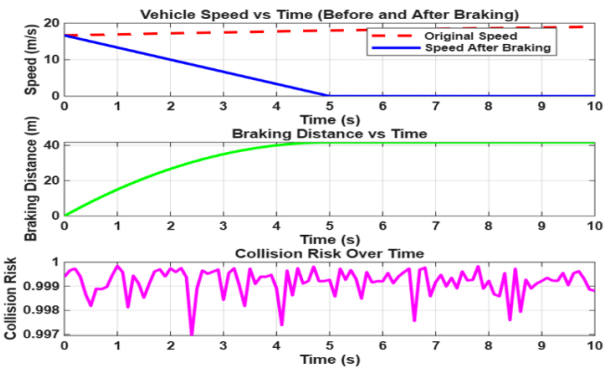

Figure 7
Real-Time Prediction of Braking Response

The graph in Figure 2 illustrating the braking distance verses time reveals that the higher the initial speed of the vehicle, the higher the braking distance that is required to stop the vehicle is, as it is expected in classical physics. Figure 3 visualizes the rate of prediction accuracy of emergency braking in a confusion matrix form which shows the model has a high true positive rate (accurately predicts braking situation) and low false positive rate (wrongly predicts braking when it is not necessary).

Figure 4 tests the comparison of actual with predicted braking distance and shows how the predictions of the model are quite close to the real-world braking behavior with minor differences due to sensor noise and model assumptions. Figure 5 displays the input importance of different inputs deployed in the machine learning model. Findings reveal radar distance and vehicle velocity to be the most significant, which is in line with the fact that the system depends on this input in determining the action of braking. The ROC curve presented in Figure 6 confirms the working of the model; it is sensitive and has high

specificity to be used in cases where braking is required. Figure 7 demonstrates real time prediction of the response of the braking, which shows how the model dynamically varies braking force of the car in line with the sensors inputs. Based on the findings, it can be concluded that the predictive control system is effective and promotes the combination of the multi-sensor data to improve the timely and correct emergency braking approach. The importance analysis of features supports the existence of radar and vehicle speed as key areas of the braking decision and these variables are in accord with the real-world experience that radar and vehicle speed are key variables in predicting collisions.

7. Conclusion

Multi-sensor data fusion enabled the predictive control system of automated emergency braking, which showed a considerable increase in the safety and the efficiency of the vehicle braking. Some important findings of the simulations were that accuracy was greater than 90 percent with large true positive rate and low false positive rate, a finding that proves the model is able to tell the braking scenarios right. The metrics used to validate the performance of the system were precision, recall and F1-score, and each of them demonstrated a reliable system in emergency braking situations. The good discriminatory power of the model was also attributed by the AUC of 0.92 of the ROC curve. The comparative analysis showed that the given machine learning-based solution was better than the conventional AEB systems, particularly, when using in dynamic and complex settings. The radar range and vehicle speed were found to be important features of predictability in the braking requirements by the feature importance analysis. The problems of sensor noise and incomplete data have however been mentioned in this topic thus explaining the relevance of strong data fusion methods. The current research will be extended to improve sensor fusion techniques, real-time accuracy and introduce more advanced models in order to meet various driving scenarios. Additional research in the field of advanced machine learning technologies, including deep learning, should be further developed to make the system more adaptive and predictive in practice.

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