

Smartphone-Based Collision Alert System for Motorcyclists

Dr. Shashikala S V
HOD & Professor
Computer Science & Engineering
BGS Institute of Technology
Adhichunchanagiri University
hodcse@bgsit.ac.in

Suhas R
20CSE082
Computer Science & Engineering
B GS Institute of Technology
Adhichunchanagiri University
suhasrumakantha65@gmail.com

Abstract: The primary aim of this study is to develop a FCW system tailored for motorcyclists. This system is designed to identify potential collisions by analyzing the time-to-collision and trajectories of both the detected vehicles and the motorcycle itself. The development encompasses three distinct approaches. Firstly, the time-to-collision metric is derived using input from a cost-effective camera. Secondly, the trajectory of detected vehicles is forecasted based on video data represented in 2D pixel coordinates. Thirdly, the lean direction of the motorcycle, vital for trajectory prediction, is determined using data from a low-cost inertial measurement unit sensor. The culmination of these approaches results in an integrated Advanced FCW system. For the prediction of time-to-collision, a nested Kalman filter is employed in conjunction with vehicle detection techniques, converting image pixel data into relative distance, velocity, and time-to-collision information. To forecast the trajectories of detected vehicles, various algorithms were evaluated, with LSTM demonstrating superior performance on the dataset. Lastly, it was determined that measuring the lean angle of the ego vehicle is more effective for determining its leaning direction than employing riding pattern classification methods.

Keywords— Forward Collision Warning (FCW), Trajectory Prediction, Lean Angle Measurement

1. INTRODUCTION

In recent years, advancements in vehicle safety technologies, particularly in the realms of autonomous driving and also Advanced Driver Assistance Systems, have promised significant reductions in road traffic accidents (RTAs) and associated fatalities. However, despite these technological strides, the grim reality persists: the global incidence of RTAs has surged, as reported by the World Health Organization (WHO), with casualties escalating from 1.25 to 1.35 million between 2015 and 2018. This disheartening trend underscores a critical gap between technological innovation and its impact on road safety, particularly in less developed nations where 93% of road fatalities occur. One pivotal barrier to the widespread adoption of advanced safety systems like ADAS lies in their prohibitive cost, primarily driven by the need for an array of expensive sensors. Consequently, those who stand to benefit the most from such safety features—individuals in regions with higher incidences of RTAs—often lack the financial means to access them. Compounding this issue is the fact that conventional ADAS solutions are predominantly tailored for conventional vehicles, neglecting the safety needs of Vulnerable Road drivers such as motorcyclists and cyclists, who constitute over 50% of global road fatalities. To address this pressing disparity, there is an urgent imperative to develop cost-effective ADAS solutions that can cater to the safety needs of VRUs. In this context, leveraging the ubiquitous presence of smartphones emerges as a promising avenue. The ubiquity of smartphones equipped with sensors, such as monocular cameras and Inertial Measurement Units (IMUs), presents a ripe opportunity to democratize advanced safety features for VRUs.

This paper aims to fill this critical gap by proposing an innovative approach to forward collision warning (FCW) systems specifically designed for VRUs. By harnessing the capabilities of commonplace smartphone hardware—namely, monocular cameras and IMUs—our proposed FCW system seeks to deliver robust collision detection and warning functionalities to motorcyclists and cyclists. Through this endeavor, we endeavor to democratize access to life-saving safety technologies and contribute to a tangible reduction in global road traffic fatalities. Despite the proliferation of advanced safety technologies, the persistently high incidence of road traffic accidents underscores the need for innovative solutions that transcend the barriers of cost and accessibility. Traditional ADAS solutions, while effective, remain out of reach for many due to their high cost and limited compatibility with vehicles commonly used by VRUs. Consequently, there is a glaring need to rethink the paradigm of vehicular safety and explore alternative avenues that prioritize affordability and inclusivity. Our proposed FCW system represents a paradigm shift in the approach to vehicular safety, leveraging the widespread adoption of smartphones to empower VRUs with life-saving capabilities. By harnessing the existing sensors embedded in smartphones, we sidestep the need for expensive dedicated hardware, democratizing access to advanced safety features for motorcyclists and cyclists alike. This approach not only addresses the financial barriers to access but also capitalizes on the familiarity and ubiquity of smartphones among VRUs, enhancing the feasibility and acceptability of our proposed solution. Furthermore, our FCW system holds the potential to serve as a catalyst for broader societal impact beyond mitigating road traffic fatalities. By equipping VRUs with enhanced collision detection and warning capabilities, we empower individuals to make safer choices on the road, fostering a culture of proactive risk mitigation and responsible driving behavior. Moreover, the deployment of our system has the potential to alleviate the burden on

healthcare systems and infrastructure strained by the aftermath of road traffic accidents, ultimately contributing to healthier and more resilient communities

2. RELATED WORK

A. Nested Kalman filter based on forward collision warning

Nested Kalman Filter it is a type of filtering technique that is used to determine the state of a system based on a group of observations and measurements. In the context of forward collision warning systems, a Kalman filter can be used to predict the trajectory and potential collision of a vehicle based on sensor data and other inputs. The Nested Kalman Filter algorithm is a recursive algorithm that consists of two types of filters: an inner filter and an outer filter. The inner filter is used to determine the state of the system based on a group of measurements, while the outer filter is used to determine the parameters of the inner filter. The Nested Filter algorithm is particularly useful for forward collision warning systems because it can account for the uncertainty and variability of the environment, such as changes in road conditions or weather patterns. The algorithm can also adapt to changes in the vehicle's dynamics, such as changes in speed or direction, to provide accurate and timely warnings to the driver. The vehicle detection method employed will utilize the You-Only-Look-Once (YOLO) detection algorithm due to its outstanding performance, processing up to 244 frames per second (fps) with a mean average precision (mAP) of 78.6%, as demonstrated by Redmon et al. The YOLO output provides boundary box coordinates, from which the width and height of the box will be extracted for distance estimation, while the center coordinates will aid in trajectory prediction. In this study, it is assumed that the disparity between the left and right limits of the bounding box corresponds to the pixel width of the car.

B. K-Filter to stabilize determined the relative distance and speed

A K-Filter is a mathematical algorithm that is commonly used for determining the present dynamic of a dynamic system based on a group of measurements. In the context of vehicle safety systems, such as forward collision warning or adaptive cruise control, K- Filters can be used to estimate the relative distance and speed between two vehicles. To stabilize the determined relative distance and also speed, a K- Filter can be used to incorporate multiple sources of data and to filter out noise and other sources of error. The K- Filter operates by estimating the state of the system on a set of measurements, and then using this estimate to predict the next state of the system. In the case of estimating the relative distance and also speed between two vehicles, the K- Filter can use sensor data from radar, lidar, and other sources to estimate the current position, velocity, and acceleration of both vehicles. The algorithm can then use this information to determine the relative distance and also speed between the two vehicles, and to predict their future positions and velocities. To stabilize the determined relative distance and also speed, the K-Filter can incorporate additional data sources, such as GPS or map data, to improve the accuracy and reliability of the estimates. The filter can also use adaptive filtering techniques to adjust the filter parameters based on changes in the environment or other factors.

3. PROPOSED SYSTEM

The proposed system aims to revolutionize vehicular safety by developing an advanced Forward Collision Warning system tailored specifically for VRUs, such as motorcyclists and cyclists. At its core, the system harnesses the ubiquitous presence of smartphones, capitalizing on the inherent capabilities of monocular cameras and Inertial Measurement Units (IMUs) found in these devices. By leveraging smartphone hardware, the proposed FCW system circumvents the need for costly dedicated sensors, thereby democratizing access to life-saving safety features for VRUs. The system comprises three key components, each contributing to the overall effectiveness and reliability of collision detection and warning functionalities. The first component involves real-time analysis of video input from the smartphone's monocular camera to detect and track nearby vehicles and potential collision threats. Through computer vision algorithms, the system extracts relevant features from the video stream, such as vehicle position, size, and relative velocity, enabling accurate assessment of collision risks. In parallel, the second component focuses on trajectory prediction, aiming to forecast the future paths of both detected vehicles and the VRU's own trajectory. Leveraging the rich sensory data provided by the smartphone's IMU, including acceleration, orientation, and angular velocity, the system employs predictive algorithms to anticipate the movements of surrounding vehicles and extrapolate the VRU's trajectory based on current dynamics and steering inputs. By integrating trajectory predictions into the collision risk assessment process, the system enhances its ability to preemptively alert VRUs to potential collision threats, allowing for timely evasive maneuvers. The third component of the proposed system revolves around the fusion of data from multiple sensors and predictive models to generate comprehensive collision warnings tailored to the VRU's specific context and risk profile. Through sophisticated fusion algorithms, the system integrates information from the monocular camera and IMU, alongside contextual data such as road conditions and traffic flow, to derive a holistic understanding of the VRU's environment and the associated collision risks. This multidimensional approach enables the system to provide nuanced and contextually relevant warnings, optimizing the balance between alerting VRUs to genuine threats and minimizing false alarms. To enhance the robustness and reliability of the proposed FCW system, several advanced techniques and methodologies are employed. For instance, machine learning algorithms are utilized to continuously refine and improve the system's object detection and trajectory prediction capabilities, leveraging large-scale datasets to iteratively optimize performance. Additionally, sensor fusion techniques, such as Kalman filtering and Bayesian inference, are employed to integrate information from disparate sensors and predictive models, mitigating uncertainties and enhancing the overall accuracy of collision risk assessments. Furthermore, the proposed FCW system incorporates adaptive and customizable features to cater to the diverse needs and preferences of VRUs. Users can personalize the system's alert thresholds,

sensitivity levels, and warning modalities to align with their individual risk tolerance and situational awareness preferences.

4. SYSTEM ARCHITECTURE

System design involves delineating the structure, components, connections, and data of a system to meet predefined criteria. It can be viewed as applying systems theory to the creation of products. There's a certain intersection with fields like systems analysis, systems architecture, and systems engineering. The proposed system architecture comprises several interconnected modules to enable a forward collision warning (FCW) system for motorcyclists and cyclists using smartphone sensors. Initially, vehicles are detected using the YOLO algorithm, with subsequent steps including pixel width calculation for relative distance and speed estimation, refinement through a first K- filter, time-to-collision calculation, and data filtering. Finally, a nested K- filter is employed for further refinement of time-to-collision estimates. This systematic approach aims to enhance road safety by providing timely collision warnings based on accurate vehicle detection and trajectory analysis using readily available smartphone hardware.

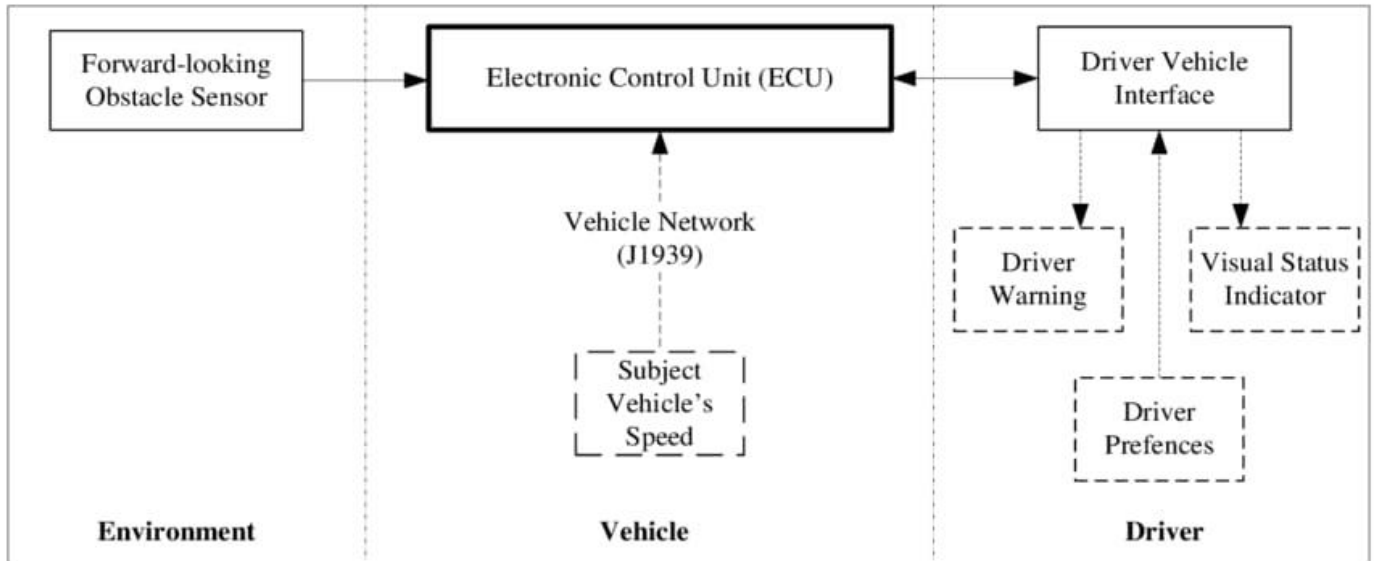


Fig 1. System Architecture

- 1. Forward Looking Obstacle Detection:** This module is responsible for detecting obstacles in the path of the vehicle using sensors like cameras or radar.
- 2. Electronic Control Unit (ECU):** The ECU processes data from the obstacle detection module and other vehicle systems to make decisions and issue warnings.
- 3. Vehicle Network:** This is the communication network within the vehicle that allows different components to exchange information.
- 4. Subject Vehicle Speed:** This component provides real-time speed data of the subject vehicle to the ECU.
- 5. Driver Vehicle Interface:** This interface allows interaction between the driver and the vehicle systems, such as setting preferences or receiving warnings.
- 6. Driver Preference:** This module captures the preferences set by the driver regarding warning thresholds or other system parameters.
- 7. Visual Status Indicator:** It provides visual feedback to the driver regarding the status of the FCW system or any detected obstacles.
- 8. Driver Warning:** This component issues warnings to the driver when potential collisions are detected or when other critical situations arise.

5. METHODOLOGY

1. Dataset Acquisition and Preparation:

- Gather a diverse dataset of video recordings captured from a smartphone mounted on a motorcycle or bicycle, encompassing various road and traffic conditions.
- Annotate the dataset to label vehicles and ground truth their positions, sizes, and trajectories for training and evaluation purposes.

2. Vehicle Detection using YOLO:

- Implement the YOLO (You Only Look Once) algorithm to detect vehicles in the video frames.
- Train the YOLO model using the annotated dataset to accurately localize vehicles and classify them within the scene.

3. Pixel Width Measurement and Relative Distance/Speed Estimation:

- Develop algorithms to calculate the pixel width of detected vehicle bounding boxes in the video frames.
- Utilize geometric principles and camera calibration parameters to convert pixel width to estimated relative distance from the smartphone and compute relative speed based on temporal changes in vehicle position.
- First K- Filter for Distance and also Speed Estimation Refinement:
- Design and implement a Kalman filter to fuse sensor measurements (pixel width) and refine estimates of vehicle distance and also speed.

4. Time to Collision Calculation and Data Filtering:

- Develop algorithms to compute time-to-collision (TTC) based on the refined estimates of relative distance and speed.
- Implement thresholding and filtering techniques to remove outlier data points and mitigate the impact of sensor noise on TTC calculations.

5. Nested K- Filter for Time to Collision Refinement:

- Design and implement a nested K- filter to further refine the estimation of time-to-collision.
- Integrate refined distance and speed estimates from the first Kalman filter with additional contextual information (e.g., vehicle acceleration, road conditions) to enhance TTC predictions.

6. System Integration and Evaluation:

- Integrate the individual modules into a cohesive software framework for real-time collision warning generation.
- Evaluate the performance of the FCW system using both quantitative metrics (e.g., accuracy, false positive rate) and qualitative assessments in simulated and real-world scenarios.
- Conduct field testing with motorcyclists and cyclists to gather user feedback and validate the effectiveness and usability of the system .

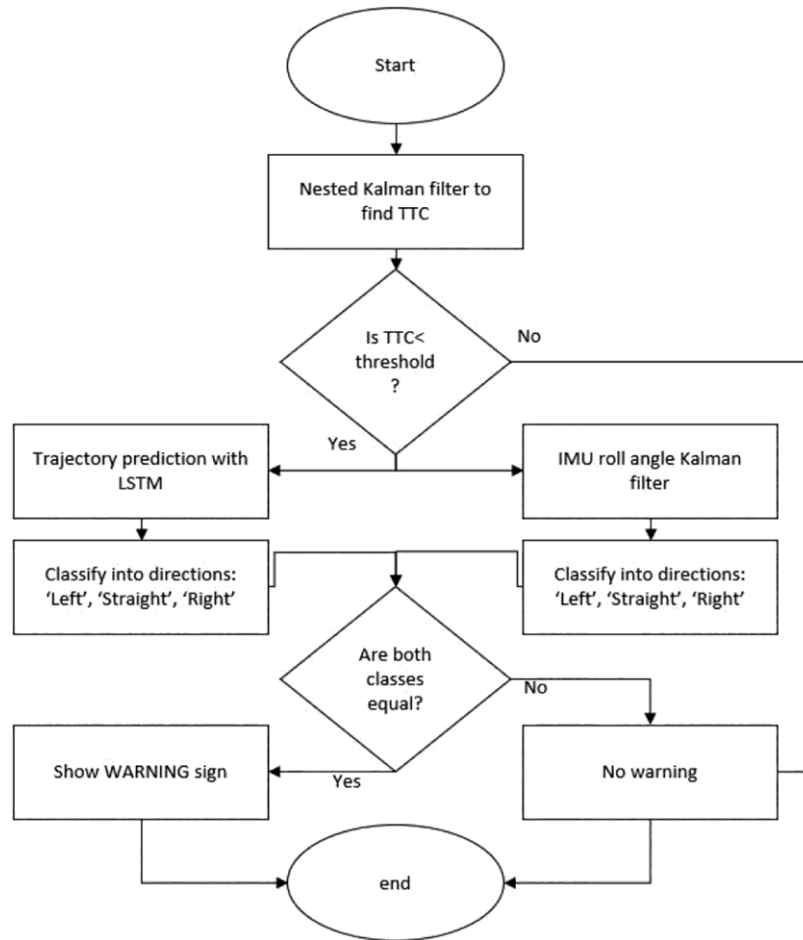
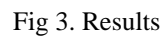


Fig 2. Flow chart

6. RESULTS AND DISCUSSION

The study delved into classifying riding patterns using 10 Hz IMU data, processed with specific time steps and under-sampling techniques. Initially, the dataset comprised six classes, including various maneuvers and straight-line riding. However, during evaluation, it became evident that distinguishing between subtle maneuvers like "Left lane change," "Right lane change," and "Moving straight" was challenging due to the continuous forward motion during lane changes and the subtle lean required for such maneuvers. To address this challenge, the dataset underwent refinement by excluding "Left lane change" and "Right lane change" classes. This refinement significantly improved the classification accuracy of both LSTM and SVM models, achieving 83.0% and 80.3%, respectively. While these accuracy levels suggest room for improvement, especially with larger datasets and extended training durations, the enhancements signify the potential of riding pattern classification in predicting leaning direction. Particularly, patterns indicative of "Left turn" & "Right turn" can correlate with left & right leans, respectively. The findings emphasize the importance of preprocessing and refining datasets to enhance the effectiveness of riding pattern classification. By focusing on discernible patterns and eliminating ambiguous classes, the classification models demonstrated improved accuracy and reduced confusion. This approach not only bolsters the reliability of predicting leaning direction but also lays the groundwork for more nuanced analysis of motorcycle riding behavior.

Moreover, the study underscores the significance of riding pattern classification in augmenting motorcycle safety systems. By accurately identifying riding maneuvers and leaning directions, such systems can offer proactive warnings and assistance to riders, thereby mitigating accident risks and enhancing overall road safety. Additionally, the study highlights the necessity of ongoing research and refinement in this field, including expanding datasets and exploring advanced machine learning techniques to further enhance classification accuracy and predictive capabilities.



The conclusion of this research is to create a novel FCW system specifically designed for Vulnerable Road Users (VRUs), such as motorcyclists. The study delineates the distinct elements of an Advanced FCW system, offering flexibility for standalone or integrated deployment. Findings indicate a significant decrease in false alarms for time-to-collision alerts, a pivotal enhancement for motorcyclist safety. Furthermore, employing solely a monocular camera and an IMU sensor in this advanced FCW system bolsters its practicality and accessibility, facilitating potential integration into smartphones without necessitating costly supplementary hardware.

REFERENCES

- [1]. Schulz, J., Hubmann, C., Löchner, J. and Burschka, D. (2018), "Multiple model unscented Kalman filtering in dynamic Bayesian networks for intention estimation and trajectory prediction", *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 1467-1474.
- [2]. Sulandari, W. and Yudhanto, Y. (2015), "Forecasting trend data using a hybrid simple moving average-weighted fuzzy time series model", *2015 International Conference on Science in Information Technology (ICSITech)*, pp. 303-308.
- [3]. Goli, S.A., Far, B.H. and Fapojuwo, A.O. (2018), "Vehicle trajectory prediction with gaussian process regression in connected vehicle environment?", *2018 IEEE Intelligent Vehicles Symposium (IV)*, pp. 550-555.
- [4]. Hossam-E-Haider, M., Islam, T., Islam, M.S. and Shajid-Ui- Mahmud, M. (2017), "Comparison of complementary and Kalman filter based data fusion for attitude heading reference system", *AIP Conference Proceedings*, vol. 1919, doi: [10.1063/1.5018520](https://doi.org/10.1063/1.5018520).
- [5]. Lauren, S. and Harlili, S.D. (2014), "Stock trend prediction using simple moving average supported by news classification", *2014 International Conference of Advanced Informatics: Concept, Theory and Application (ICAICTA)*, pp. 135-139.
- [6]. Lim, Q., He, Y. and Tan, U. (2018), "Real-time forward collision warning system using nested Kalman filter for monocular camera", *2018 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pp. 868-873.
- [7]. Lim, Q., Johari, K. and Tan, U. (2019), "Gaussian process auto regression for vehicle center coordinates trajectory prediction", *TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON)*, pp. 25-30.
- [8]. Park, S.H., Kim, B., Kang, C.M., Chung, C.C. and Choi, J.W. (2018), "Sequence-to-sequence prediction of vehicle trajectory via LSTM Encoder-Decoder architecture", *2018 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1672-1678.
- [9]. Radziukynas, V. and Klementavicius, A. (2014), "Short-term wind speed forecasting with ARIMA model", *2014 55th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCon)*, pp. 145-149.
- [10]. Redmon, J., Divvala, S., Girshick, R. and Farhadi, A. (2016), "You only look once: unified, Real-Time object detection", *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 779-788.