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Pedestrian safety system with crash prediction

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***Abstract*---**Every year nearly 1.5 million people are dying in traffic collisions around the world, due to the unexpected behavior of pedestrians while crossing the road. To address this problem an augmentation function for predicting the crash risk of the active pedestrian is proposed. The augmentation function has several functions like pre-crash scenario, vehicle trajectory, and pedestrian trajectory. In a Pre-Crash scenario, pedestrian movement such as entering the road boundary or not is detected. The input comes from the sensor which is located at the head of the car. After the pre-crash scenario vehicle trajectory is used to control the speed of the vehicle. Then the Markov IRW model-based pedestrian trajectory finding is used to predict the state of each pedestrian. The states are categorized into three types: Running, Walking and Standing. In this model, the pedestrian types whether the pedestrian is a child or young or old aged people is predicted. And the crash risk is evaluated based on the Monte Carlo algorithm that calculates the minimum detection range for active pedestrians. If the crash risk is exceeded the threshold limit then an augmentation function is activating the evasive action. If the evasive action flag is raised the speed rate must be reduced or change the lane.

***Keywords*---**augmentation function, crash prediction, Markov model, pedestrian safety.

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Introduction

In recent years, 1.35 million people died in road traffic accidents around the world, with pedestrians accounting for 23% of those killed.In 2020, around 6000 pedestrians were killed in traffic accidents in the United States. On average, for every 1.5 hours one pedestrian is dead in road accidents. As a result, most automobile builders have developed and implemented active pedestrian safety systems (APSS) in the vehicles in order to reduce and eliminate pedestrian collisions. The sensor system keeps an eye on the pedestrian in front of the vehicle. The augmentation function calculates the possibility of striking a pedestrian in the near future based on all of the pedestrian's possible random paths.The pedestrian in this case was walking down the road or standing by the side of the road with no apparent intention of crossing, but suddenly leaped out and was struck by a passing car for unknown reasons.

Related Works

The author Leopoldo AR Mesto et.al [1] proposed the Advanced driver assistance system (ADAS). Every year, accidents involving buses or coaches result in thousands of damages and causalities. To lessen their frequency and severity, A haptic throttle pedal and crisis decelerating are proposed for an advanced driving assistance system (ADAS).It also presents a computationally efficient approach based on three essential concepts: a simpler but accurate vehicle model, a collision detection system that is efficient, and an efficient collision avoidance system that takes into accounta danger assessment system that generates warnings and emergency braking signals, as well as the driver's intent and pedestrians roving around the car Finally, the proposed ADAS is put to the test in a driving virtual realitycompartment with a simulated urban scene and real-life bus components. The findings show a statistically substantial boost in safety, with a decrease in the incidence of crashes and high-risk scenarios, an improvement in the response time to the brake pedal, and an increase in the time to collision in emergency situations. The planned ADAS on municipal buses might theoretically improve safety by reducing the number and severity of pedestrian collisions.In this project they are use Warning and Braking algorithm. This algorithm shows iterative procedure to determine collision risk factor.In [2] Juan Dols et.al proposed the Haptic Feedback to Assist Bus Drivers for Pedestrian Safety at Low Speed for Passenger Transportation Systems (PTS). Buses and coaches are the most common forms of the passenger transportation system (PTS) in the European Union, accounting for more than half of all land PTS. From this given the fact that bus accident rates are lower than other modes of transportation, their size and weight increase the severity of bus accidents, even at low speeds. Turning and manoeuvres around bus stops are the most common causes of collisions in metropolitan areas due to low visibility, blind spots, and driver distractions. As a result, there is an increasing interest in developing driving assistance systems to avert these and other scenarios. Even while such solutions exist, they are not designed to operate at low speeds in urban contexts with the sole objective of preventing pedestrian collisions. The research proposes an active safety approach for buses undertaking low-speed manoeuvres in this area. Haptic feedback devices, as well as crash avoidance and risk assessment algorithms based on persons spotted near the bus, are all part of the safety system.In a simulated urban scenario, the active safety system's output was validated. The proposed low-speed active safety system decreases driver reaction time while increasing time to collision, according to our findings. The number of high-risk cases and collisions has reduced, signifying a considerable gain in safety, according to the findings. There is also a brief discussion of new regulations regarding enhanced safety technologies on real autos. They are using an obstacle avoidance algorithm in their project. It's utilized to deliver particular speed directives in order to prevent colliding with other vehicles.

In [3] Christoph G. Keller proposed the Object identification system called Active Pedestrian Safety by Automatic Braking and Evasive Steering. By warning the driver and/or exerting automatic vehicle control ahead of collisions, active safety systems have the ability to minimize accident frequency and severity. This study introduces a new active pedestrian safety system that syndicatesidentifying, scenario investigation, decision-making as well as automobile control. The sensor element is based on stereo vision and contains the subsequent two complementing techniques for additional sturdiness:1) Object identification based on motion and 2) foot walker recognition. The method's most impressive feature is its capacity to decide whether to undertake autonomous brake system or evasive steer mechanism in a split second and to do so consistently at high vehicle speeds (up to 50 km/h). On the test track, we conducted comprehensive pre-crash tests with the system (22 scenarios with real pedestrians and a dummy). The combination of foot walker recognitionwith the motion-based object detection enhanced the detection accuracy and lateral velocity estimation significantly. In more than 40 trials on a completely reproducible setup including a fake that laterally move in the motor vehiclelane from behind an obstruction, the system conducted the required vehicle function, i.e. autonomous brake system (if a full stop is still possible) or automated evasive steer mechanism.In this project they are using stereo algorithm. This algorithm used to identify individual objects and to acquire motion of recognized objects. They are also using 6D-vision algorithm for reconstruct the 3D motion field.

In [4,] Chao Zhu et al introduced the Boosted Multi-Task Model for Pedestrian Detection with Occlusion Handling, an occlusion-specific detectors system. In computer vision, detecting pedestrians is a tough task, although it has made substantial progress in recent years. Existing state-of-the-art techniques, on the other hand, experience significant performance degradation when the number of pedestrians occluding them grows. A conventional way for obstructionsupervision is to train a number of occlusion-specific indicators and then directly combine their findings, but these sensors are proficient individually and the association between them is ignored. We regard foot walkeridentification at varying occlusion stages as a collection of related but unique issues in this study, and we recommend anenhanced multi-task prototype to account for both their similarities and variances.A multi-task learning technique is used in the proposed model to map foot-travelers at varying occlusion levels to a public room, where all prototypes for dissimilar levels of occlusion are limited to share a common set of characteristics, and a boosted detector is then used to differentiate people from the surrounding environment. The counseled approach is examined on 3 difficult pedestrian identity facts sets: INRIA, TUD-Brussels and Caltech and it outperforms the literature's today's on a number occlusion-precise take a look at sets. In their project, they use Multi-Task LDCF Model Learning to handle occlusion. It will investigate two binary classification tasks: pedestrians with less than 35% occlusion and pedestrians with less than 80% occlusion.

The visual cues-based system was proposed by Wanly Ouyang et al. in [5.] This work addresses the challenging subject of recognizing pedestrians in crowds. A novel method is recommended for single-pedestrian detection with multi-pedestrian detection. A multi-pedestrian detector mixing model is intended to capture the unique graphical cues created by surrounding pedestrians that single-pedestrian detectors miss. A probability based method is used to represent the association between the configurations projected by single- and multi-pedestrian detectors, and the result of the single-pedestrian detection is improved by using multi-pedestrian detection. 25 state of the art single-pedestrian detection methods are integrated with two-pedestrian detector on three different widely used public datasets: ETH, TUD-Brussels andCaltech. According to the results of our tests, our technology strengthens both of these ways. In terms of average miss rate, the Caltech-Test dataset improves by 9%, the TUD-Brussels dataset improves by 11%, and the ETH dataset improves by 17%. The percent of0 37 to 32 is the lowest average miss rate on the Caltech-Test dataset, TUD-Brussels dataset percentage values from 55 to 50, ETH dataset percentage values from 43 to 38.

Proposed System

The Figure 1 depicts a high-level overview of device architecture in which the pedestrian distance and angle values are determined from the corresponding sensor and those values are used to determine the minimum detection range between the car and the pedestrian, after which we proceed to the pre-crash scenario for foot-travellers crashes by deciding if the pedestrian is in the field of view, which is determined by this module. Vehicle simulation Trajectories are used to calibrate a vehicle's speed in order to assess the likelihood of a collision. Estimation of Accident Risk is used to refine the time it takes for a person to enter the collision zone and it takes time for a vehicle to reach the collision zone, all of which arecalibrated by this module.

Pre-Crash Scenario for Pedestrian Crashes

The vehicle's field of view is crucial because the proposed system defines a range of two angles from 20° to 60° in which the pedestrian faces a crash risk and it is depicted in figure 2.. So, using values such as vehicle acceleration, distance, time to reach the collision by car, and time to reach the collision by a pedestrian, the condition is run to determine if the pedestrian is on the road or on the platform. These values are averaged and compared, and the results are used to determine if the pedestrian was struck by a car or not, and the function variable is set to 1 if the pedestrian was hit, otherwise 0.It is computed using equation 1 and 2.

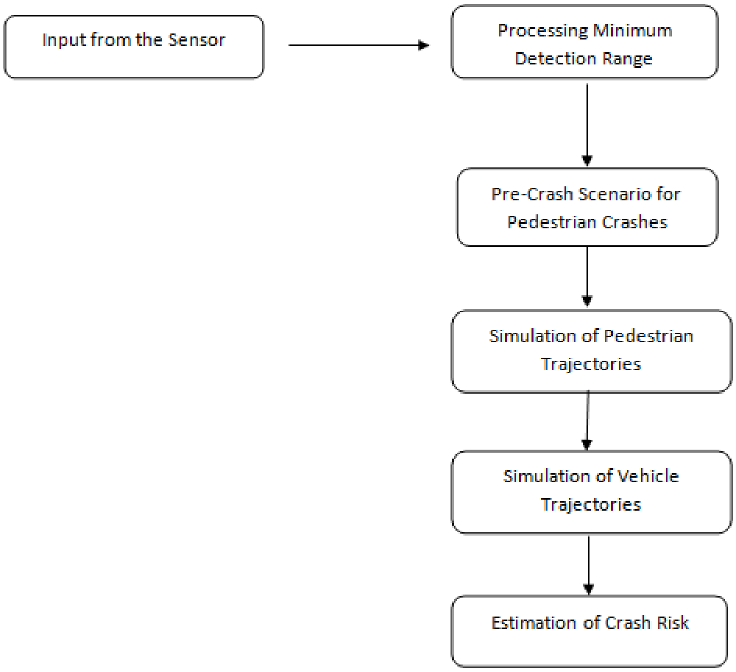

Figure 1. System architecture

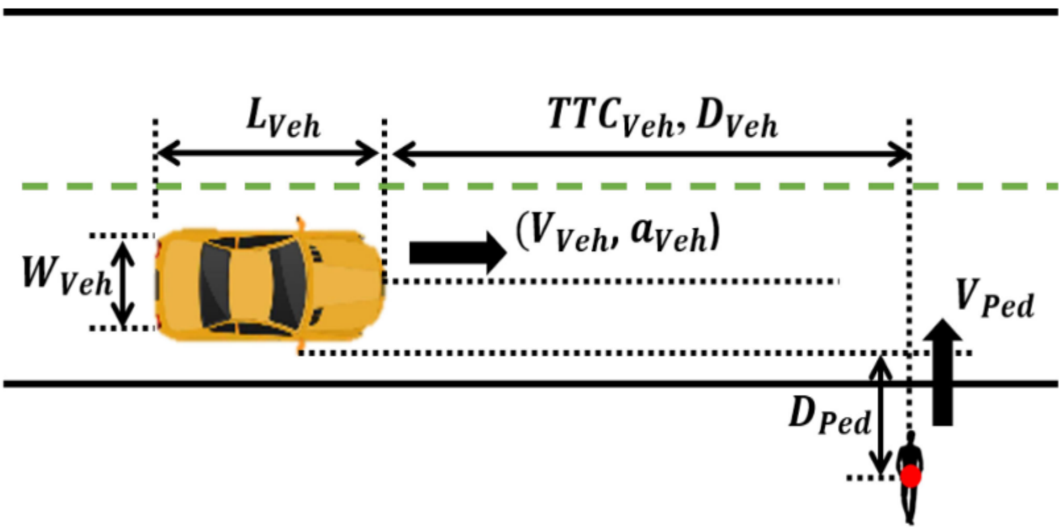

Figure 2. Pre-crash scenario configuration

$$\begin{aligned}&If\ (1/2t_{pr}^2 a_{veh} + t_{pr}V_{veh} * L_{veh} < TTC_{veh} * V_{veh})\&\&(TTC_{veh} * V_{veh} < 1/2t_{pe}^2 a_{veh} + t_{pe}V_{veh})\\ &\text{then}\quad f(D_{ped}, TTC_{veh}, V_{veh}, V_{veh}, t_{pr}, t_{pc}) = 1 \\ &Else\quad f(D_{ped}, TTC_{veh}, V_{veh}, V_{veh}, t_{pr}, t_{pc}) = 0\end{aligned} \tag{1}$$

Probability of a pedestrian hitted by a Vehicle is computed as

$$\frac{\Sigma V_{veh}\,\Sigma t_{pr},t_{pe}\,f(D_{ped},TTC_{veh},V_{veh},t_{pr}t_{pe})}{\Sigma V_{veh}\,\Sigma t_{pr}t_{pe}} \quad (2)$$

Vehicle Trajectories Simulation

The vehicle trajectory configuration uses the formula to calculate the vehicle's speed between 20Km and 60 Km, with an average calibrated value of 40Km.The driver can apply the vehicle's maximum declaration of 9.8 m/s for emergency braking, reducing only the possibility of a pedestrian collision.

$$f(V_{veh}) = \frac{1}{\sqrt{2\pi * 20.2^2 * 0.68}} e - ½((V_{veh} - 20)/20.2)^2 \quad (3)$$

Simulation of Pedestrian Trajectories

The first step in pedestrian trajectories is to categorize pedestrians into three classes: Children, young people, and the elderly. These groups are separated by age (5-9) (10-59) (over 60). These are all values, and pedestrian trajectories design's main objective is to quantify and assess the pedestrian's pace, which is divided into three states: standing,walking, and running.

$$n_t \times per = \sum_{i=1}^{n} ni \times Normdist(v_{per}, \mu_i, \sigma_i) \quad (4)$$

By measuring the speed of all aged people like Child, Young and Old on other hand evaluating the speed of N people, and the step size value is calibrated as 1 step/0.5 s. Every stage is calculated by the algorithm as Markov IRW, which uses the initial speed, target speed of the pedestrian, road boundary, heading position of the pedestrian, time to reach the collision zone, and time to reach each phase size to decide which state the pedestrian is detected and the next state of the pedestrian.

$$a_x = \frac{(v_{target} - v_{initial})}{\mathrm{T}} * cos\,(\theta_{initial} + \Delta\theta) \quad (5)$$

The longitudinal value is calculated by above formula [5]which comprises the initial state speed of the pedestrian and is subtract with the target state speed of the pedestrian and we take the ΔΘ which have the value of head position of the initial state and target state both are subtract and added with the Θ initial and this value is take the trigonometry function as cos and all estimated value is divided by time which take to cross the collision zone of the road so this is the main context of this formula and that is passed into the Monte Carlo algorithm above the formula is calibrated continuously stored and it update the pedestrian location and speed whether the pedestrian entirely cross the collision zone.

Estimation of Crash Risk

To calculate the likelihood of a collision, the Monte Carlo technique is utilised. This function is used to calculate the distance between the pedestrian and the collision zone, as well as the time it would take for the vehicle to cross the collision zone, and there is an evasive flag variable also counted.If the pedestrian is in a collision zone and the time required to cross it, the value (D_{ped}, TTC_{veh}) is tracked and expected, and the minimum detection range is calibrated, the final outcome would be to adjust the vehicle's lane or decrease the speed of the vehicle.

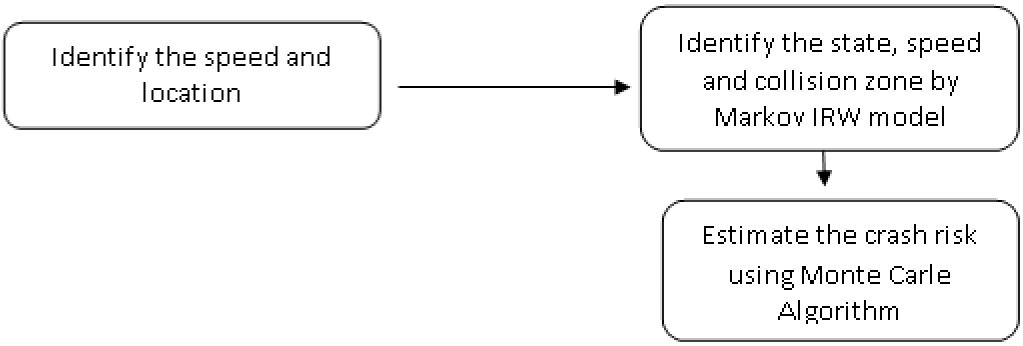

Figure 3. Crash Risk Evaluation overflow

In order to estimate the crash risk assessment performance, evasive acts such as lane change or speed reduction are recommended, depending on the pedestrian type, such as children, elderly people, and children of a young age. Our project's effective performance is a combination of speed reduction and lane shift, which decreases the likelihood of a crash. Figure 3 shows the crash risk mitigation values.

Pedestrian State Simulation

The pedestrian state simulation is implemented as a Markov Integrated Random Walk (IRW) algorithm, which is used to monitor pedestrian movement in each inter or intrastate evolution. There are three states Standing still, walking, and running. These three states vary in terms of speed and timing. Initialize the pedestrian position, current state, speed, heading direction, and road boundary in this algorithm. Select the next state of the pedestrian and change the heading direction from initial to next state with the probability function if the current state does not equal "Running" depending on the current state. And the ages of the various categories are calibrated using previous comparisons, and these values are used to categorize individuals into different age groups such as Child, Young, and Old. Each pedestrian state does have its own speed. A humdrum has a target hustle and directionpath in each state, with the complete values being impacted exclusively by the current condition.The target speed was supposed to be consistent between subsequent stages of the same sort, although the heading direction could change as the state progressed.The movement of a pedestrian in each intra and inter-state progression was tracked using aunified random walk (IRW) model.Using independent motion controllers in both longitudinal and lateral directions, this prototype can recreate multifacetedhumdrum behaviour in a humble yet realistic manner. The longitudinal motion control needed to be well-matched with the pre-crash scenario, hence equation [6-9] was used to calculate it.

$$px\ (t\ + \Delta\ t) = px\ (t) + \Delta\ t * \ vx\ (t) \tag{6}$$

$$vx\ (t\ + \Delta\ t) = vx\ (t) + \Delta t\ *\ ax\ +\ \Delta t\ *\ \ \omega x(t) \tag{7}$$

$$ax\ = \frac{(vtarget\ - vinitial)}{T} * cos\ (\theta initial\ + \Delta\theta) \tag{8}$$

$$\omega x\ (t)\ \sim WGN\,(0, \sigma^2 x) \tag{9}$$

The heading direction is main the thing for this technique depending upon the head directions pedestrian state is identified whether he or she is in running or walking or standing still these all are the activities found by this algorithm.

Markov- IRW Model

The pseudo-code is as follows

1) Track and assignthe pedestrian location, current state to be "Standing still," speed $V_{initial}$ and heading direction ϴ initial and prepare road boundary
2) do loop:
3) If your current state isn't "running," then:
4) Predict the next state and adjust the going direction Δθ based on the current state from state i to state j with probability $P_{ijangle}$
5) Ifthe initial state equals to next state:
6) Make target speed V_{target} to be unchanged
7) Else:
8) Predict the target speed (V_{target}) next state with probability (Pj)
9) For t=0.1, T do
10) Update location of pedestrian and speed execute formula from (6) ~ (9)
11) If a pedestrian crosses the road's edge:
12) Change the next state to "running" andthen
13) terminate the loop
14) If the current state is "running":
15) Change θ=0
16) While pedestrians do not cross the road's edge do:
17)Don't change the target speed (V_{target})
18) For t=0.1, T do
19) Updatelocation of pedestrian and speed execute the formula from (6) ~ (9)
20) If pedestrian enters road boundary
21) terminate
22) Change heading direct θ=0
23) Change thepedestrian location and speed based on function(6) ~ (9)
24) If a pedestrian crosses the road's edge:
25) terminate
26) Updatethe next state to be current

Before choosing to cross the lane, the pedestrian made a random movement along the roadside, as well as a sufficiently synchronized movement when darting into the road, were both utilized in the above Markov IRW algorithm. Because the vehicle speed is continuously changing per minute, pedestrian movement is very important to track to avoid the crash risk. And Markov IRW model is finding the multiple active pedestrian's states and their speed, heading direction, so it checks the road boundary every time if the pedestrian entries into the road boundary this algorithm finds their speed initial location and longitudinal direction also, that longitudinal direction is for calculating the pedestrian is in the safe zone or collision zone. Meanwhile, higher-speed and inter-state evolutions would have more unpredictability than slower and intra-state evolutions.

Crash Risk Estimation

Monte Carlo Algorithm

1) Collection up a set of pedestrian places along the road's edge, D_{ped}.
2) Give the pedestrian a collection of vehicle locations, TTC_{veh}.
3) Do the following for any (D_{ped}, TTC_{veh}) pair.
3) pedestrian trajectory Traj p based on Morkov-IRW model (Algorithm 2)
4) Take a sample of V_{veh} (vehicle speed) from the formula (4)
5) Do any(V_{veh}, Traj p) pair for any(V_{veh}, Traj p) pair.
6) If formula (2) is correct, then:
7) Crash event count+=1
8) Using the formula, determine the FOV and detection range (1)
9) Calculate the Risk of a Crash
10) Choose a critical (D_{ped}, TTC_{veh}) pair to work with.
11)Calculate percentilee FOV and detection range

According to the Monte Carlo approach, small and large D_{Ped} values imply that the foot-walkers can stand on the vehicle's near and far sides, respectively. The TTC_{Veh} measured between 0.5 and 5.0 seconds and roofed the most of the vehicle's foot-walkers approaches. The Markov-IRWmodel was used to sample the pedestrian trajectory, which was selected from a distribution specified by formula (4). A safety buffer was built into the W_{Veh}, which was set to 2.59m. At 4.88m, the L_{Veh} was picked. Speed reduction and lane shifting were also investigated as evasive actions.

Experimental Results

The figure 4 depicts the Crash Risk graph for Children in walking state. The minimal criteria for supporting the augmentation function are a field of vision of 50° and a discovery range of 40 m, which needs an upgrade for many APSSs now in use by car manufacturers.Even if there is no immediate conflict with the pedestrian, the augmentation task will initiate obliqueactivities if the dangerof crashingexceeds a tolerable level.If the accident risk probability is more than 0.1, the driver should change the vehicle's lane or lower the vehicle's speed. The reason for changing the lane of the vehicle and speed reduce the crash risk. If the crash risk is reduced the accident also reduced.

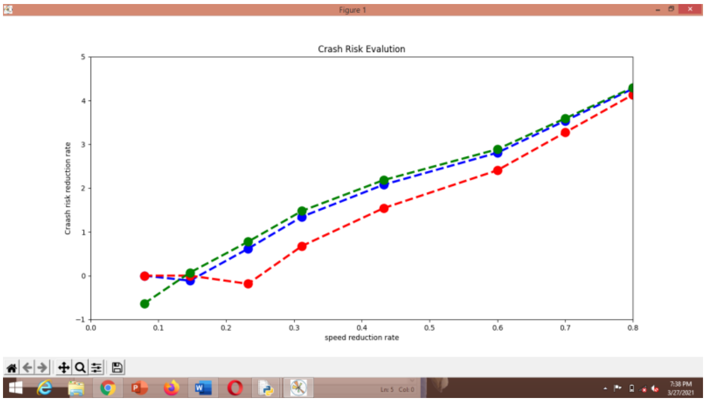

Figure 4. Crash Risk graph for Children in walking state

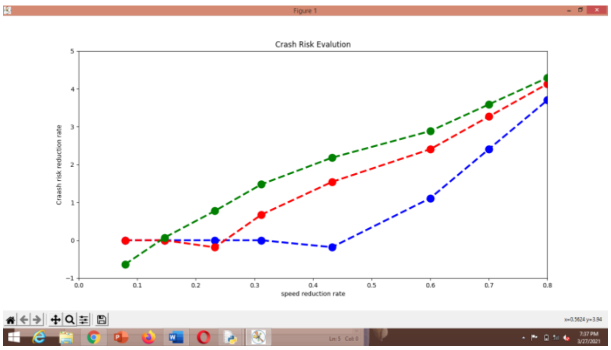

Figure 5. Crash Risk graph for Old people in Running state

The figure 5 represents the and Crash Risk graph for old people in running state. The crash risk can be reduced by changing the vehicle lane and hence the accident can be avoided in future.

Conclusion

In this analysis, an augmentation mechanism for conventional APSSs was proposed to increase device efficiency in the edge situation, where a pedestrian darts out abruptly without warning. Traditional APSSs are triggered when a pedestrian engages in actual conflict conduct, such as entering the vehicle lane. The vehicle-to-pedestrian conflict occurs quickly in the researched edge scenario, making it impossible for the standard APSS to make timely manoeuvres to avoid an accident. Using CNN motion-contour-image-based HOG-like descriptors and Support vector machine approaches, we anticipate being able to define a foot walker's overpasspurpose using accurate head and body postures as data in the future.

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