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Transforming Accident Detection through Vision-Based Traffic Surveillance System and Deep Learning

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ABSTRACT: This study aims to revolutionize the identification and analysis of traffic accidents using surveillance cameras by implementing the entire architecture on an AI demo board. The first step involves locating destroyed cars through the motion interaction field (MIF) technique, which detects collisions in videos based on interactions among multiple moving objects. Next, the YOLO v3 model is employed to determine the precise location of the damaged vehicles. Utilizing a hierarchical clustering technique, the vehicle trajectories before and after the collision are retrieved. To aid traffic officials in decision-making, these trajectories are then transformed into a vertical view using perspective transformation.

The vehicle velocity is calculated using the unbiased finite impulse response (UFIR) method, eliminating the need for statistical understanding of background noise. The investigation of traffic accidents can leverage the estimated velocity and collision angle obtained from the vertical perspective. Finally, to demonstrate the effectiveness and performance of the proposed technique, a test is conducted using the HiKey970 Huawei AI demo board. This board is programmed with all the aforementioned algorithms, and various accident surveillance videos serve as input for the demo board, showcasing efficient accident recognition and retrieval of relevant vehicle trajectories

Keywords : Accident detection, speed estimation, target tracking, unbiased finite impulse response (UFIR) filter, vehicles

I. INTRODUCTION

The use of traffic monitoring technologies to find and assess incidents has become more and more important over the past few decades. At the traffic management centre, TMC, human observation is mostly used for crash detection. Manual observation has a variety of shortcomings even if it is frequently reliable. On the one hand, it is impossible for individuals to quickly identify every accident in the entire city, which implies that the injured in a traffic accident may frequently not be treated properly. Manual investigation of a traffic accident's cause On the other hand, because it is challenging to determine the trajectory and speed from surveillance footage, collision can occasionally be incorrect. Systems for automatically identifying and studying traffic accidents are therefore needed.

Over the past two decades, vision-based collision detection techniques have changed in three different ways: by predicting traffic flow patterns, analysing vehicle behaviour, and modelling vehicle interactions [1]. The first method uses massive data sets of traffic laws to model typical traffic patterns. Accidents are defined as situations in which a vehicle's trajectory deviates from typical trajectory patterns [5]–[7]. The lack of real-world collision trajectory data makes it difficult to detect collisions, though. The second method analyses vehicle motion data [8–10], such as speed, acceleration, and the space between two cars, to identify accidents.

This method implies that all moving vehicles must be continuously observed. Consequently, the method's precision in a Processing power is frequently a constraint in situations of crowded traffic. The third method uses the social force model [11] and the intelligent driver model [12] to represent vehicle interactions. Since it only recognises collisions based on changes in vehicle speed, this strategy necessitates

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a high number of training samples yet has low accuracy.

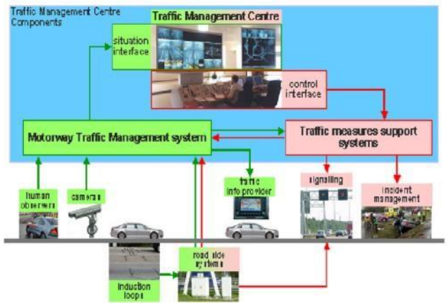

Figure 1:Traffic Management system

II. LITERATURE REVIEW

Bangji Zhang[1]in his study addressed the importance of steering angle and sideslip angle as crucial conditions for vehicle handling and stability control are covered in the text. The paper suggests an indirect estimating method to make vehicle control systems more affordable rather than explicitly measuring these angles. A novel observer design that simultaneously estimates the steering angle and sideslip angle replaces the conventional model-based techniques used to estimate the sideslip angle with the measured steering angle. The observer is created using the Takagi-Sugeno (T-S) fuzzy modelling technique, with a nonlinear Dugoff tyre model and time-varying vehicle speed used to represent the model of the vehicle's lateral dynamics. . Applications for the estimated angles include autonomous steering control, steering system problem detection, and tracking driving efficiency.

Haiping Du[2] proposed a novel approach that makes use of an intelligent driver model to locate aberrant traffic patterns. The method entails modelling particles as automobiles in a video sequence and utilising the intelligent driver model to analyse their behaviour. Latent Dirichlet allocation is used to learn the behaviours, and frames are categorised as abnormal or not based on a likelihood threshold. A Finite Time Lyapunov Field is created and spatial behaviour gradients are computed to pinpoint the problem. The watershed method is then used to segment the area of irregularity. With the use of videos downloaded from stock footage sources, the effectiveness of the suggested strategy is verified.

Anirudha V Bharadwaj[3]The abstract discusses the necessity of precise angular velocity (AV) estimation in a variety of applications, including spacecraft monitoring and speed control. Although linear velocity estimation is thoroughly studied, it is difficult to estimate AV for randomly moving objects with different speeds. For AV computation, non-contact-based techniques are in great demand. An enhanced algorithm for real-time AV estimation using a live video feed is presented in the suggested work.The proposed method demonstrates a significant improvement when compared to the Lucas Kanade (LK) object tracking method for AV estimation, specifically for motion in circles.

Jan-Shin Ho[4]in their study discuss about the unbiased Average Traffic Speed (UARTS) estimation for intelligent transportation systems is a new technique that is presented in this research. In contrast to conventional techniques, UARTS uses probe cars that are GPS and radar gun equipped to transmit their position, time, and the speeds of nearby vehicles to a control centre for maximum-likelihood estimate. This method guarantees that the speed distribution of the probe vehicles has no impact on estimation accuracy. A genuine data experiment is also compared the UARTS estimator's accuracy to that of the conventional ARTS estimator.

Jagannadan Varadarajan[5]in his study introduces a brand-new topic model for identifying and comprehending events in intricate surveillance settings. The model takes into account local rules that form temporal links between past and present activity occurrences, as well as global scene states that specify which activities can occur. A binary random variable is used to include these elements into a probabilistic generative process. . The model's capacity to forecast upcoming actions and associated lag times provide insightful information about the dynamics of the surveillance scene

SHANG Mingli[6]discussed about predicting the vehicle's side slip angle, a crucial component of vehicle stability control, this research suggests a hybrid observer. A state-space observer, a kinematics integration module, and a weight distribution module make up the hybrid observer. A vehicle stability sensing module and a fuzzy controller are both included into the weight distribution module. The fuzzy controller computes the weight of the state-space observer depending on the vehicle's stability status after determining the vehicle's stable status using the phase plane approach.

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Hou-Ning Hu[7]In this paper discussed about a brand-new online system for 3D vehicle tracking and detection from monocular films is presented. The framework estimates moving vehicle's complete 3D bounding box information from a series of 2D photos in addition to associating moving vehicle detections over time. For accurate instance association, the method uses 3D box depth-ordering matching, and it makes use of 3D trajectory prediction to re-identify obscured vehicles.

Yuriy S. Shmaliy[8]The filtering, smoothing, and prediction issues in discrete time-invariant models in state space are addressed by the generic -shift linear optimum Finite Impulse Response (FIR) estimator presented in this study. By resolving the discrete algebraic Riccati problem, the initial mean square state function is identified, and the best solution is then produced in batch form. The suggested solution may be expressed in batch and recursive forms and doesn't require any prior knowledge of the noise or initial state. It is also impartial. The noise power gain (NPG), which can be computed quickly thanks to a recursive approach, is used to calculate the mean square errors of the estimations.

Akisue Kuramoto[9]In order to safely design a route during autonomous driving, it is essential to precisely calculate the 3D coordinates of far-detected vehicles, which is what this study describes. A 3D camera model is created utilising the vehicle plane and distortion settings to map pixel coordinates to distance values. By utilising the derivative relationship between the camera and world coordinate systems, an Extended Kalman Filter (EKF) framework is created to follow the detected vehicles in order to increase distance accuracy.

Kimin Yun[10]In this research, a unique approach to modelling the interaction of several moving objects is presented for the detection and localization of traffic accidents. The technique is modelled after how water waves respond to objects on the surface. The Motion Interaction Field (MIF) is a field that use Gaussian kernels to depict the motion of the water surface. Traffic accidents can be located and recognised using the MIF's symmetric features without the use of intricate vehicle tracking. The suggested strategy beats current approaches in terms of accuracy for identifying and localising traffic incidents, according to experimental results

III . METHODOLOGY

A.DATASET DESCRIPTION

The dataset was assembled from a variety of resources, including accident files that were made publicly available, dashcams, and traffic surveillance cameras. It includes a variety of geographical settings, such as urban, suburban, and highway settings. A representative sample of accident scenarios is ensured by the length of the data gathering period, which is several months.High-resolution cameras placed in key areas were used to take pictures, giving a complete picture of the traffic circumstances. To provide a broad dataset that represents actual accident scenarios, various weather, illumination, and road characteristics were taken into account. Additionally, each image had metadata that included the date, time, and place.

B. DATA PREPARATION AND LABELLING

There are a number of classes that categorise various accident kinds and severity levels in the dataset for accident detection. The descriptions of each class are as follows:

1. Car Accident:Images from collisions involving two or more automobiles fall under this category. It encompasses situations in which vehicles crash with one another sideways, rear-on, or from the front. The involved automobiles may sustain varying degrees of damage as a result of these collisions.

2.Moderate: Pictures of incidents with a moderate degree of severity are included in the moderate accident class. These mishaps frequently involve collisions of two or more automobiles or other substantial impacts, although the resulting harm and injuries are usually not serious. Examples might include collisions that result in minimal damage, dented cars, or minor injuries.

3.Moderate- Accident: This category includes incidents with a severity rating that is greater than moderate but not quite severe. These collisions could

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result in serious auto damage, people getting hurt, or a mix of both. They frequently cause traffic interruption and call for rapid treatment.

4. Object Accident: Pictures of accidents involving things, other than vehicles, are included in the object accident class. Collisions with fixed objects like walls, barricades, or road signs may occur in these mishaps. Instances where objects fall onto the road, creating a hazard for cars and perhaps resulting in accidents, might also be included.

5.Severe Accident: Pictures of incidents with a high degree of severity are included in the severe accident class. These mishaps frequently entail severe collisions that cause serious vehicle damage, participation of several vehicles, and serious injuries or fatalities. Emergency services are frequently needed after serious accidents, and traffic interruptions can linger for days or even weeks.

6. Severe-Severe Accident: Accidents in this category are classified as having a very high level of severity. These mishaps sometimes include severe collisions, such as rollovers, high-speed collisions, or mishaps involving huge vehicles like buses or trucks. They frequently lead to serious injuries, fatalities, massive car damage, and major traffic interruptions.

Researchers and developers can train machine learning models to detect and categorize accidents based on their severity by categorizing incidents into distinct classes. This aids in the creation of efficient accident detection systems and enhances emergency response protocols.

C.PROPOSE SYSTEM

In this article, we present a method for accident analysis and detection that may be used with AI demo boards. A motion interaction field (MIF) model is used to swiftly identify and locate traffic events. We use a YOLO v3 model and hierarchical clustering to determine the path taken by the car before to the collision. We employ unbiased finite impulse response (UFIR) to estimate the speed and contact angle of the involved vehicles before the collision.To accurately evaluate the event, filtering and viewpoint alteration are used. Additionally, we evaluated the framework on HiKey970, a Huawei AI showcase board, in terms of system implementation.

Advantages:

1. An experiment is run utilising a Huawei AI demo board called HiKey970, which is used to write all of the aforementioned algorithms, to show the effectiveness and implementation performance of the provided technique.

2. Various accident surveillance movies are used as input for the demo board. Effective accident recognition and retrieval of pertinent vehicle trajectories.

A. Motion Interaction Field

The MIF model is used to identify accidents and locate the involved automobiles. MIF is a traffic detection methodology that Yun [4] has suggested. The model's inspiration is the when several items are moving on the water's surface and pushing the water around and making waves, the water waves move [4]. All interactions between moving objects in films are reflected in the MIF. After applying an optical flow technique to determine the speed and location of each moving point, the MIF is produced using Gaussian kernels. If the maximum of MIF, also known as an abnormality, exceeds the threshold after MIF filtering, a traffic collision can be found and recognised. This approach avoids sophisticated training that requires a large amount of training data and powerful processing. Thus,It fits inside our framework. Figure 3 depicts the method's general structure.

The following is a summary of our method's steps.(Optical Flow) Step 1: Utilise the optical flow algorithm to obtain each object's position (xi, yi), speed (vxi, vyi), and direction (vxi, vyi).

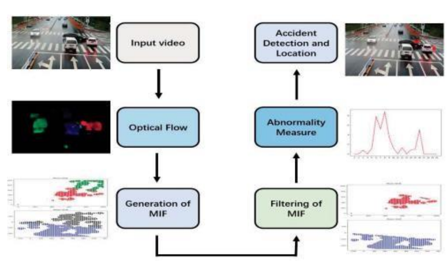

Figure 2:Overall framework of the MIF model.

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Step 2 (MIF generation): Subtract two Gaussian functions with various centre positions to provide the kernel k(x, y, xi, yi) and (xi + V_{xi}, yi +V_{yi}) is one central position that indicates the forward direction. The second is

Representing the reverse way is (xi-V_{xi}, yi-V_{yi}).

$$K(x, y; x_i, y_i) = k(x, y; x_i + v_{x_i}, y_i + v_{y_i}) - k(x, y; x_i - v_{x_i}, y_i - v_{y_i}). \quad (1)$$

MIF is the sum of all kernels obtained in (1)

$$F(x, y) = \sum_{x_i, y_i} K(x, y; x_i, y_i) \quad (2)$$

B. YOLO v3

The YOLO v3 model is used to identify the transport vehicles in the correct location after the detection and localization of crashed vehicles. A CNN network for object detection is the YOLO network. Our YOLO v3 network is 416 416 in size in accordance with the unified size of traffic surveillance footage, which balances recognition speed and accuracy.

The YOLO v3 model in this framework solely identifies vehicles, motorcycles, and trucks to prevent interference from other items. The input to the network is the image to be detected, and YOLO v3 [32] can be used to produce the coordinates and probabilities of each bounding box. The following diagram shows the YOLO v3 network's structure.

$$\text{confidence} = P_r(\text{Object}) \times \text{IOU}_{b-\text{box}}^{\text{truth}} \quad (3)$$

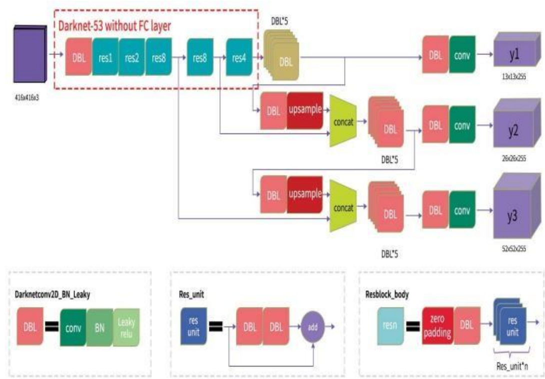

Figure 3: YOLO v3 network.

C. Hierarchical Clustering

A clustering process called hierarchical clustering does not require a predetermined number of clusters. It creates several hierarchies by dividing the datasets. At first, each endpoint is in its own cluster. The hierarchy is then raised until the termination condition is satisfied after which the paired clusters are combined into a single one [33]. The procedure for hierarchical clustering is depicted in Fig. 5. The image of the accident car in each frame serves as the dataset for the proposed framework's hierarchical clustering algorithm. The clustering results can be used to determine the trajectory.

$$\text{distance}_1 = \sqrt{\sum_i (a_i - b_i)^2} \quad (4)$$

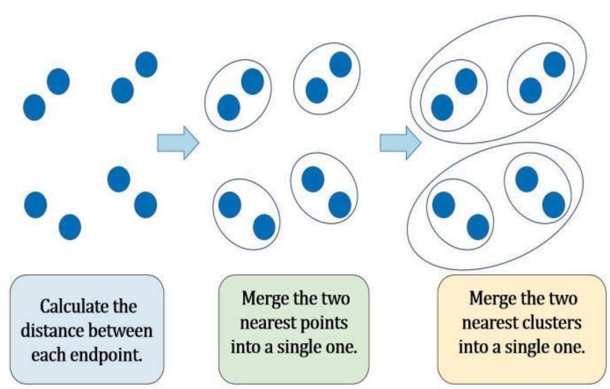

Figure 4:Hierarchial Clustering process

D.UFIR Filtering

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The output of the UFIR filter is bounded for all bounded inputs. When a digital signal with arbitrary amplitude-frequency characteristics is input, the UFIR filter may operate without knowing any information about the noise and guarantee that the phase-frequency characteristic of the output digital signal stays absolutely linear. The UFIR filter's unit impulse response, meanwhile, is limited. Therefore, our framework can make the trajectory smooth by using the UFIR filter.

IV. IMPLEMENTATION:

YOLO V5:

The item identification method known as YOLO, which stands for "You Only Look Once," divides pictures into grids. The task of locating objects within a grid cell belongs to each grid cell. YOLO is one of the most well-known object detecting methods due to its quickness and accuracy. High-performance object detection is accomplished using YOLO (You Only Look Once) models. YOLO divides a picture into grids, and each one labels objects inside of itself. They can be used for real-time object detection depending on the data streams.

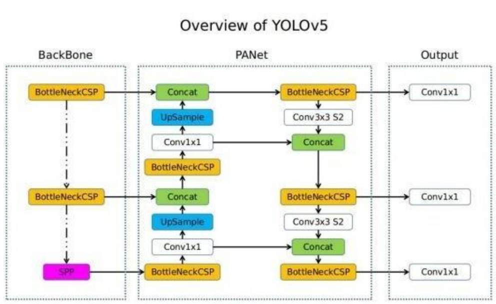

Figure 5: Overview of YOLOv5

As a Convolutional Neural Network (CNN) Scheme, the YOLOv5 Architecture. The main parts are the backbone, neck, and head. The Backbone uses CSPNet to extract features from the photographs used as input photos. The pyramid feature is made with the Neck feature

V. CONCLUSION

This study provided a mechanism for automatically locating and assessing traffic incidents in video data. First, crashes in films were identified and located using the MIF model approach. Second, a YOLO v3 model was used to the identification of wrecked cars. Third, the trajectories before the collision were retrieved using the hierarchical clustering method. To facilitate the decision-making of traffic officers, the trajectory projections were transformed into a vertical representation from a horizontal one. The vehicle velocity was ascertained after the trajectories underwent UFIR filtering. The predicted speed and the accident's impact angle was then assessed from a vertical perspective. Finally, a hardware practise test was conducted using the Huawei AI demo board HiKey970 to code all of the aforementioned algorithms. A video from an accident surveillance system provided the demo board's input. The accident was correctly identified, and the corresponding vehicle trajectories were gathered. HiKey970 performed 28.85%-45.72% better than the Intel Core i7-9750H CPU @ 2.60 GHz system.

VI. FUTURE WORK

The future will need to deal with a few challenges, though. Another deep learning model could be used to start with in order to improve recognition precision when the car is blocked. Second, various picture enhancing techniques can be applied to increase the efficacy of accident detection in a variety of meteorological conditions or when the quality of surveillance recordings is subpar. Third, the licence plate of the vehicle involved in the crash can be found for more research. Course tracking control and threat detection for autonomous vehicles will be the focus of our future work.

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