

A Vision-Based System Design and Implementation for Accident Detection and Analysis via Traffic Surveillance Video

Mrs. CH. Veena¹, M. Swathi², M. Harini³, M. Rujula⁴

¹Assistant Professor, Computer Science and Engineering, Sridevi Women's Engineering College Hyderabad, India

Email id: ¹veena.stars@gmail.com

²Computer Science and Engineering, Sridevi Women's Engineering College, B.Tech IV Year Hyderabad, India.

Email id: ²swathimunagapati1@gmail.com

³Computer Science and Engineering, Sridevi Women's Engineering College, B.Tech IV Year Hyderabad, India.

Email id: ³harinimeka10@gmail.com

⁴Computer Science and Engineering, Sridevi Women's Engineering College, B.Tech IV Year Hyderabad, India.

Email id: 4rujulachoudary005@gmail.com

ABSTRACT:

In this work, we aim to investigate the problem of detecting and analyzing traffic accidents automatically and effectively through surveillance videos and implement the whole framework on an AI demo board. First, the technique of motion interaction field (MIF) that has the potential to detect crashes in a video is adopted to locate the crashed vehicles based on the interactions between multiple moving objects. Second, the YOLO v3 model is employed to identify the crashed vehicles within the appropriate location. In order to recover the vehicle trajectories before the collision, a hierarchical clustering approach is used, and the corresponding trajectories are obtained. Third, to facilitate the judgment of traffic police, the trajectory is projected to a vertical view by using a perspective transformation. The vehicle velocity is estimated accordingly with the unbiased finite impulse response (UFIR) approach that does not require statistical knowledge of the external noise. Then, the estimated velocity and the obtained collision angle from the vertical view can be utilized to analyze the traffic accident. Finally, to show the effectiveness and implementation performance of the proposed approach, an experiment is carried out based on a Huawei AI demo board named HiKey970 that is used for coding all the mentioned algorithms. Several accident surveillance videos act as the input of the demo board. The accidents are detected successfully, and the corresponding vehicle trajectories are recovered.

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

1. INTRODUCTION

During the past decades, increasing attention has been paid to detect and analyze accidents via traffic surveillance equipment. The detection of crashes is mainly based on manual observation in the traffic management center (TMC). Although manual observation is reliable in most instances, it has a lot of shortcomings. On the one hand, it is difficult for people to detect all of the accidents in the entire city quickly, which means that the injured in a traffic accident may not be treated properly in many cases. On the other hand, the manual analysis of the cause of a traffic accident is sometimes inaccurate because it is hard

to get the trajectory and speed through surveillance video. Thus, it is necessary to develop algorithms for automatically detecting and analyzing traffic accidents.

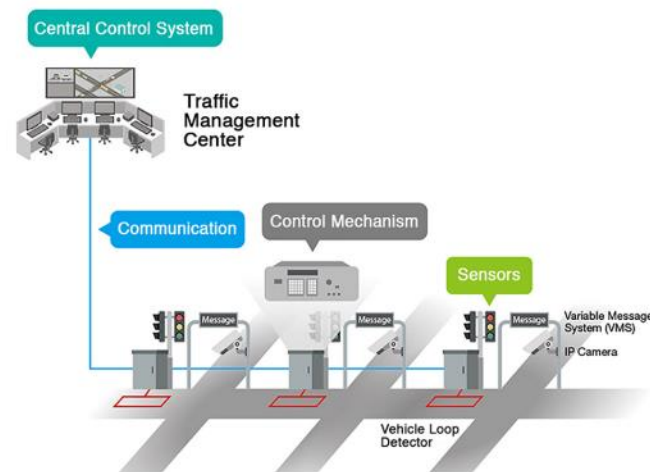


Fig.1: TMC Components

The methods of vision-based accident detection in the past two decades have been developed in three ways: modeling of traffic flow patterns, analyzing vehicle activities, and modeling of vehicle interactions [1]. In the first method, the typical traffic patterns are modeled based on traffic rules from large data samples. If the trajectory of a vehicle is inconsistent with typical trajectory patterns, it would be determined as an accident [5]-[7]. However, it is difficult to detect collisions because the trajectory data of collisions in the real world is limited. The second method detects accidents by calculating vehicle motion characteristics [8]-[10], such as speed, acceleration, and distance between two vehicles, which means that all vehicles need to be tracked continuously. As a result, the accuracy of the method in a crowded traffic environment is usually limited by computational capacity. In the third method, the interaction of vehicles is modeled with the application of the social force model [11] and the intelligence driver model [12]. This method requires a lot of training samples, and the performance is poor since it detects collision based on the change of vehicle speed only.

2. LITERATURE REVIEW

Video analytics for surveillance: Theory and practice:

Video analytics, loosely defined as autonomous understanding of events occurring in a scene monitored by multiple video cameras, has been rapidly evolving in the last two decades. Despite this effort, practical surveillance systems deployed today are not yet capable of autonomous analysis of complex events in the field of view of cameras. This is a serious deficiency as video feeds from millions of surveillance cameras worldwide are not analyzed in real time and thus cannot help with accident, crime or terrorism prevention, and mitigation, issues critical to the contemporary society. Today, these feeds are, at best, recorded to facilitate post-event video forensics.

Using the visual intervention influence of pavement marking for rutting mitigation— Part II: Visual intervention timing based on the finite element simulation

Visual intervention has a significant influence on drivers' behaviour, which may cause the redistribution of wheel tracks, relieving the stress from the concentration of axial loads so that the rutting can be mitigated, which has been introduced and validated in a companion paper (Part I). Reasonable determination of the visual intervention timing with a three-stage intervention method can reduce rutting. In this paper, an initial development rate method is proposed, and the rutting prediction method based on finite element model is

established. The data of rutting depth is segmentally fitted to obtain the rate curve of rutting deformation, based on which the intervention timings of three kinds of typical pavement structure are determined. It is found that SUPERPAVE pavement is the latest to set intervention while AC pavement is the earliest one. The analysis also shows the higher the capability of resisting rutting deformation is, the later the rutting deformation enters the second stage (steady state), which means the intervention is delayed. For the same pavement structure, the intervention of longitudinal slope section is earlier than that of flat slope section. Moreover, the service life of asphalt pavement can be prolonged by 16-31% in an intervention cycle.

Synergies of electric urban transport systems and distributed energy resources in smart cities

Transport systems and buildings are among the bigger energy users inside cities. Abundant research has been developed about these systems (facilities and transport). However, synergies among them are commonly overlooked, not taking advantage of the possible benefits of their joint coordination and management. This paper presents a linear programming model to find the optimal operation and planning of distributed energy resources (DER) in a residential district, while considering electric private and public transport systems, in particular electric vehicles and metro. Hence, the main contribution of this paper is the analysis of synergies of such an interconnected scheme. It has been assumed that part of the metro regenerative braking energy can be stored into electric vehicles' (EVs') batteries, so that it can be used later for other trains or for the EV itself. Several case studies have been proposed using data from a residential district and a metro line in Madrid. The obtained results show important cost savings in the overall system, especially a significant power cost reduction for the metro system.

Motion interaction field for accident detection in traffic surveillance video

This paper presents a novel method for modeling of interaction among multiple moving objects to detect traffic accidents. The proposed method to model object interactions is motivated by the motion of water waves responding to moving objects on water surface. The shape of the water surface is modeled in a field form using Gaussian kernels, which is referred to as the Motion Interaction Field (MIF). By utilizing the symmetric properties of the MIF, we detect and localize traffic accidents without solving complex vehicle tracking problems. Experimental results show that our method outperforms the existing works in detecting and localizing traffic accidents.

Bridging the past, present and future: Modeling scene activities from event relationships and global rules

This paper addresses the discovery of activities and learns the underlying processes that govern their occurrences over time in complex surveillance scenes. To this end, we propose a novel topic model that accounts for the two main factors that affect these occurrences: (1) the existence of global scene states that regulate which of the activities can spontaneously occur; (2) local rules that link past activity occurrences to current ones with temporal lags. These complementary factors are mixed in the probabilistic generative process, thanks to the use of a binary random variable that selects for each activity occurrence which one of the above two factors is applicable. All model parameters are efficiently inferred using a collapsed Gibbs sampling inference scheme. Experiments on various datasets from the literature show that the model is able to capture temporal processes at multiple scales: the scene-level first order Markovian process, and causal relationships amongst activities that can be used to predict which activity can happen after another one, and after what delay, thus providing a rich interpretation of the scene's dynamical content.

A Markov clustering topic model for mining behaviour in video:

This paper addresses the problem of fully automated mining of public space video data. A novel Markov Clustering Topic Model (MCTM) is introduced which builds on existing Dynamic Bayesian Network models (e.g. HMMs) and Bayesian topic models (e.g. Latent Dirichlet Allocation), and overcomes their drawbacks on accuracy, robustness and computational efficiency. Specifically, our model profiles complex dynamic scenes by robustly clustering visual events into activities and these activities into global behaviours, and correlates behaviours over time. A collapsed Gibbs sampler is derived for offline learning with unlabeled training data, and significantly, a new approximation to online Bayesian inference is formulated to enable dynamic scene understanding and behaviour mining in new video data online in real-time. The strength of this model is demonstrated by unsupervised learning of dynamic scene models, mining behaviours and detecting salient events in three complex and crowded public scenes.

A system for learning statistical motion patterns:

Analysis of motion patterns is an effective approach for anomaly detection and behavior prediction. Current approaches for the analysis of motion patterns depend on known scenes, where objects move in predefined ways. It is highly desirable to automatically construct object motion patterns which reflect the knowledge of the scene. In this paper, we present a system for automatically learning motion patterns for anomaly detection and behavior prediction based on a proposed algorithm for robustly tracking multiple objects. In the tracking algorithm, foreground pixels are clustered using a fast accurate fuzzy k-means algorithm. Growing and prediction of the cluster centroids of foreground pixels ensure that each cluster centroid is associated with a moving object in the scene. In the algorithm for learning motion patterns, trajectories are clustered hierarchically using spatial and temporal information and then each motion pattern is represented with a chain of Gaussian distributions. Based on the learned statistical motion patterns, statistical methods are used to detect anomalies and predict behaviors. Our system is tested using image sequences acquired, respectively, from a crowded real traffic scene and a model traffic scene. Experimental results show the robustness of the tracking algorithm, the efficiency of the algorithm for learning motion patterns, and the encouraging performance of algorithms for anomaly detection and behavior prediction.

3. METHODOLOGY

Several models based on deep learning have been presented for automatic traffic accident detection. These methods require training with large amounts of data and use complex neural networks to detect collisions in videos. However, limited by the amount of training data and high computational costs, these frameworks are difficult to be implemented practically. In addition, with the rise in the number of traffic surveillance videos, detecting and analyzing accidents throughout the whole city with a centralized system are difficult. It is necessary to build a distributed architecture consisting of embedded devices deployed in every block of the city. Therefore, a lightweight framework that can be implemented on embedded devices is required.

Disadvantages

1. However, limited by the amount of training data and high computational costs, these frameworks are difficult to be implemented practically.
2. In addition, with the rise in the number of traffic surveillance videos, detecting and analyzing accidents throughout the whole city with a centralized system are difficult.

In this article, we propose an accident detection and analysis framework that can be implemented on AI demo boards. Considering quick accident detection, a motion interaction field (MIF) model is adopted to detect and localize traffic accidents. Regarding the analysis of traffic accidents, we use a YOLO v3 model and hierarchical clustering to get the trajectory

of the vehicle before the collision. In order to analyze the accident accurately, we employ unbiased finite impulse response (UFIR) filtering and perspective transformation before estimating the speed and collision angle of vehicles in an accident. In addition, regarding the implementation of the designed system, we validate the framework on HiKey970 that is a Huawei AI demo board.

Advantages:

1. To show the effectiveness and implementation performance of the proposed approach, an experiment is carried out based on a Huawei AI demo board named HiKey970 that is used for coding all the mentioned algorithms.
2. Several accident surveillance videos act as the input of the demo board. The accidents are detected successfully, and the corresponding vehicle trajectories are recovered.

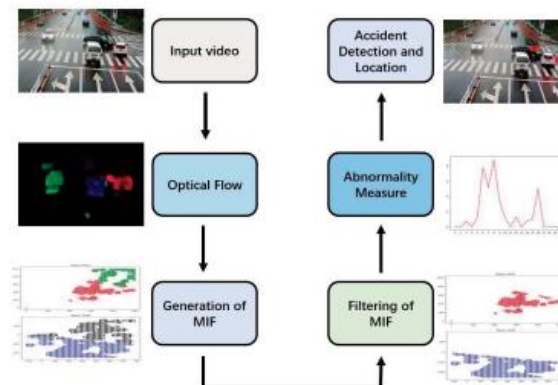


Fig.2: System architecture

MODULES:

To implement aforementioned project we have designed following modules

- Data exploration: using this module we will load data into system
- Processing: Using the module we will read data for processing
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Build YOLOV5 model.
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

4. IMPLEMENTATION

ALGORITHMS:

YOLOV5:

YOLO an acronym for 'You only look once', is an object detection algorithm that divides images into a grid system. Each cell in the grid is responsible for detecting objects within itself. YOLO is one of the most famous object detection algorithms due to its speed and accuracy. YOLO (You Only Look Once) models are used for Object detection with high performance. YOLO divides an image into a grid system, and each grid detects objects within itself. They can be used for real-time object detection based on the data streams.

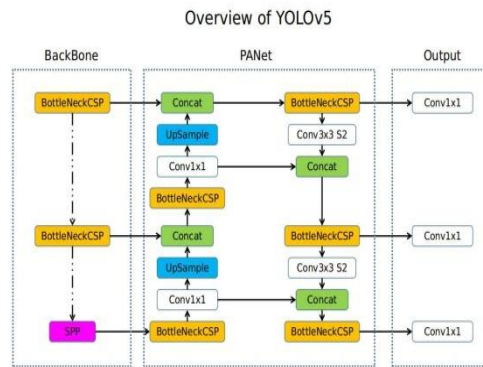


Fig.3: YOLOv5 architecture

Scheme of the YOLOv5 Architecture as Convolutional Neural Network (CNN). Main parts include the Backbone, Neck and Head. In the Backbone, CSPNet is used in order to extract features from the images which are used as input images. The Neck is used for the creation of pyramid feature.

YOLO v5 was introduced in 2020 by the same team that developed the original YOLO algorithm as an open-source project and is maintained by Ultralytics. YOLO v5 builds upon the success of previous versions and adds several new features and improvements. Unlike YOLO, YOLO v5 uses a more complex architecture called EfficientDet (architecture shown below), based on the EfficientNet network architecture. Using a more complex architecture in YOLO v5 allows it to achieve higher accuracy and better generalization to a wider range of object categories.

Another difference between YOLO and YOLO v5 is the training data used to learn the object detection model. YOLO was trained on the PASCAL VOC dataset, which consists of 20 object categories. YOLO v5, on the other hand, was trained on a larger and more diverse dataset called D5, which includes a total of 600 object categories. YOLO v5 uses a new method for generating the anchor boxes, called "dynamic anchor boxes." It involves using a clustering algorithm to group the ground truth bounding boxes into clusters and then using the centroids of the clusters as the anchor boxes. This allows the anchor boxes to be more closely aligned with the detected objects' size and shape.

YOLO v5 also introduces the concept of "spatial pyramid pooling" (SPP), a type of pooling layer used to reduce the spatial resolution of the feature maps.

5. EXPERIMENTAL RESULTS

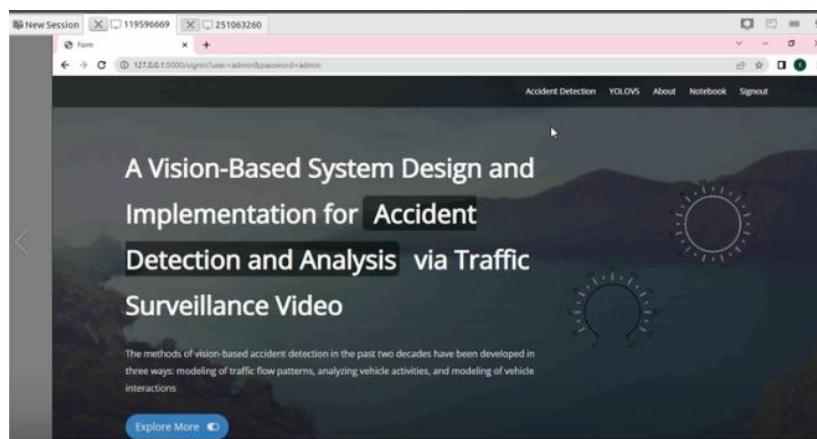


Fig.4: Home screen

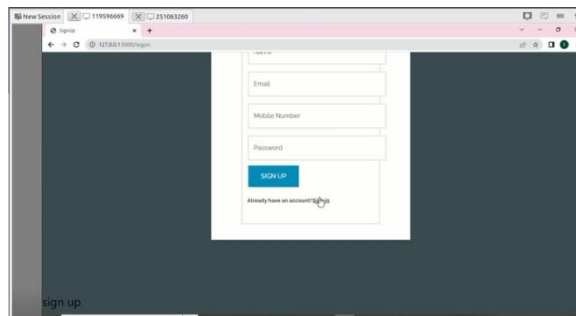


Fig.5: User registration

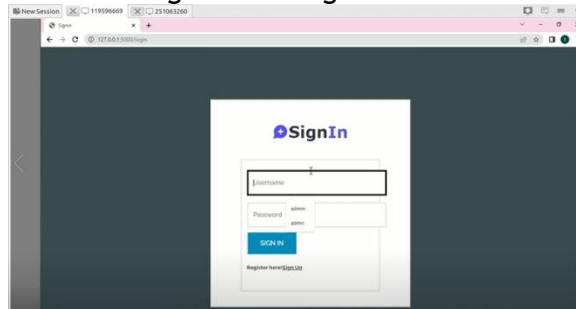


Fig.6: user login

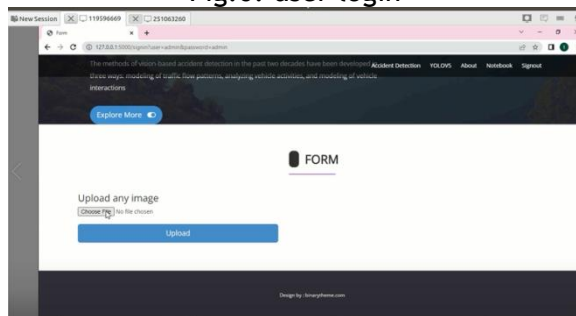


Fig.7: Main screen

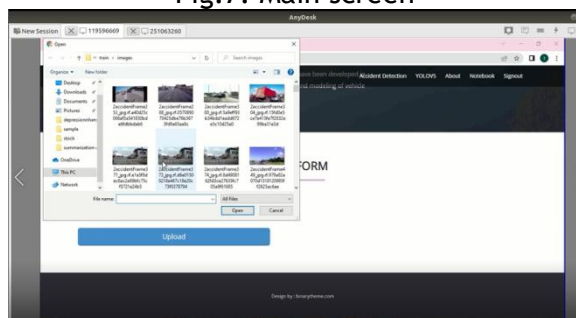


Fig.8: Input images

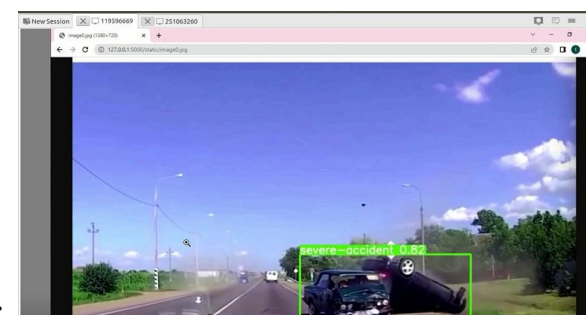


Fig.9: Prediction result

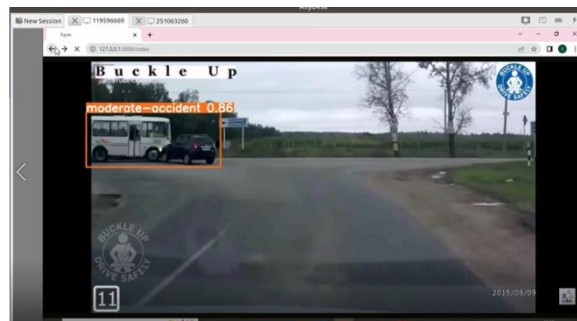


Fig.10: Prediction result

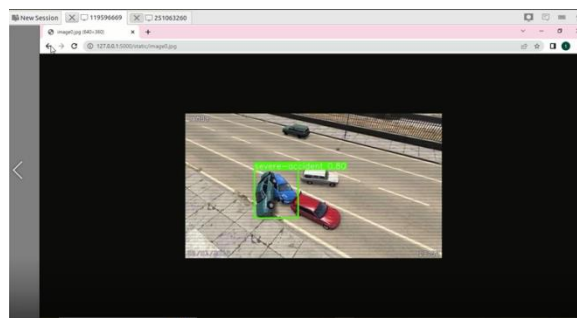


Fig.11: Prediction result

6. CONCLUSION

In this article, a framework was proposed for detecting and analyzing traffic accidents automatically through surveillance video. First, the technique of the MIF model was utilized to detect and locate crashes in videos. Second, a YOLO v3 model was adopted for the identification of crashed vehicles. Third, the hierarchical clustering algorithm was used to recover the trajectories before the collision. In order to facilitate the judgment of traffic police, the trajectories were projected to a vertical view through perspective transformation. Using UFIR filtering, the trajectories were filtered, and the vehicle velocity was estimated. Then, an accident was analyzed by the estimated velocity and the obtained collision angle from the vertical view. Finally, a hardware practice test had been carried out for coding all the mentioned algorithms on HiKey970, a Huawei AI demo board. An accident surveillance video acted as the input of the demo board. The accident was detected successfully, and the corresponding vehicle trajectories were recovered. The performance of HiKey970 was 28.85%-45.72% of Intel Core i7-9750H CPU @ 2.60-GHz system.

FUTURE WORK

However, there are still some problems to be solved in the further. First, another deep learning model can be tried to improve the identification accuracy when the car is blocked. Second, some image enhancement algorithms can be adopted for better performance of accident detection under different climate conditions or if the quality of surveillance videos is low. Third, the number plate of accident vehicles can be recognized for further analysis. In future research, we will focus more on path tracking control and attack detection for autonomous vehicles.

8. REFERENCES

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