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Semantic Video Mining for Anomaly and Mishap Scrutinizer

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***Abstract* – Video surveillance is necessary to pull out more interesting and useful information from video data set. From various applications of video surveillance the system works for accident detection from abnormal behavior of multiple vehicles on highways and notifying for the same. it is one of the most active research topics in computer vision. In this work, rapid traffic video surveillance and monitoring system are presented along with dynamic traffic signal control and accident detection mechanism. It works with the objective of producing the complete automatic intelligent system to overcome the delay expected by the human efforts in detecting accidents. To fulfill the objective moving objects are detected using background subtraction. These objects are classified to separate out the desired objects which are positive samples tracked to analyze the behavior and gen- erating the required events. The system detects accident using the vehicles stopped motion, which can be due to accident or vehicle stopped at the roadside. The accident situation can be detected by using the classifier. Thus accidents are classified automatically into major and minor accident classes and the information is sent immediately to the concerned people. For major accidents the message is sent to ambulance, police and relatives, and for minor accidents message is sent to relatives alone. The proposed intelligent traffic video surveillance system renders rapid dynamic control of traffic signals and it raises the identification of accidents correctly.**

***Keywords* – Video Mining, Intersection Collision, Semantic Video Mining.**

I. INTRODUCTION

About 1.3 million according to the annual Global Road Crash Statistics On average, 3,287 people die in road accidents every year. In these days, a large number of cameras are being installed For traffic monitoring purposes since the accident demands Identification and analysis are being enhanced. Since recent traffic The monitoring system relies mostly on human observation, it is It is difficult to monitor a large number of camera scenes At the same time and without remembering unusual events. In To overcome this limitation, a lot of effort has been made Developing an automated detection method through computer vision And pattern recognition techniques, but the current level The technology is still limited to being implemented in real environments. Current methods for traf- fic accident detection are Developed through three methods: modeling traffic flow Analysis of patterns, vehicle movements and modeling of vehicles chit chat.

Road surveillance videos provide vast detail for minute review Road conditions, classification of vehicles, road detec- tion, speed violation detection, traffic flow estimation, traffic management and collision detection aspects. We want to work on collision detection for vehicle data and road monitoring.

Video summaries are an economical way to represent video content. And has effective and quick browsing of relevant activity Video. It is extensively applied in various applications. It is used in films, Sports, news, remote encroachment, medical diagnosis and egoistic Video to summarize its content for quick browsing. In this paper, we select Key frames from videos using important illustrated video content.

As the video summary is a subjective venture, it is important to make it A summary that accompanies the general perception of the audience. In short, video must contain all the important semantic content according to human perception. Viewers do not focus on the entire image But only around a small foveation area, which has high weight properties in the video Summary compared to peripheral areas.

A large number of cameras are being used for traffic Accident detection and analysis has been sought since analysis purposes Increased. Since recent traffic monitoring systems rely mostly on human perforation- tion, it is difficult to monitor large numbers of camera scenes at the same time and to detect unusual events

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without disappearing. To overcome this limi- tation, an automatic detection method has been tried through pattern recognition techniques and computer vision, but the level of current technology is still limited to being applied in real environments. Existing methods have been developed for accident detection through these methods: the model of traffic flow patterns, the monitoring of vehicle activities, and the modeling of vehicle interactions.

II. PROBLEM DEFENITION

About 1.3 million according to the annual Global Road Crash Statistics Every year people die in road accidents, an average of 3,287 deaths per day. Increasing number of vehicles Even on the road will make the problem of road accidents worse. Surveillance cameras are The streets are ubiquitous and capture 24 hours of video. Surveillance video The streets are installed on the pole captured using surveillance cameras Along the roads. These cameras are installed to monitor Anomalies occurring on the roads. There are many cameras nearby Roads but the proposed method focuses on a single camera view that gives A clear picture of road activity. Collected huge data Consumption of cameras can be painstaking and to investigate the occurrence of a Accident scenario present in the video. It is very difficult to review the entire video to find the recorded accidents. We need to reduce the redundant nature of the video so that its content is summarized using video summary techniques.

Road surveillance videos provide vast detail for minute review Road conditions, classification of vehicles, road detec- tion, speed violation detection, traffic flow estimation, traffic management and collision detection aspects. We want to work on collision detection for vehicle data and road monitoring.

III. DATA FLOW DIAGRAM

Fig. 1. Level 0 DFD: Context diagram.

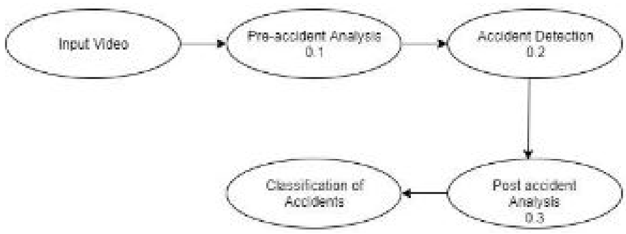

Fig. 2. Level 1 DFD.

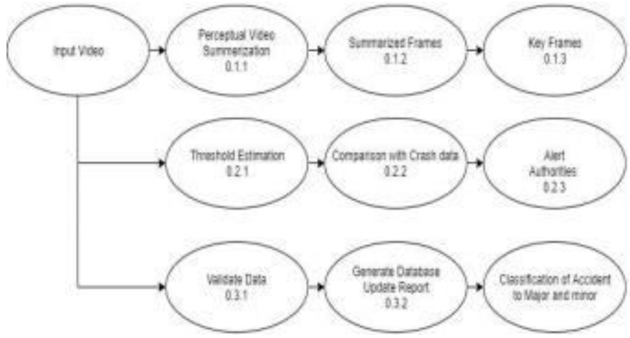

Fig. 3. Level 2 DFD.

IV. RELATED WORK

Not all road accidents are of the same type. We Study various collisions in detail in this section. This is the first time of all kinds Collisions are studied in detail. Road traffic collisions are generally classified Four Common Types:

1. Head-on Collision

A face-to-face collision is a traffic collision, where the front ends of two vehicles collide with each other. They are often classified as A fatal type of road traffic collision. This type of collision is easily detectable. The bounding box of each vehicle tube is tracked by video. In a head-on collision, Tubes of vehicles coming from opposite directions merge into one tube. The frame where the inter-tube collision cost is high predicts the crash phase. this It is difficult to disassemble the vehicle tube during the collision phase. When the trajectory merges, the size of the bounding box suddenly increases and the size is stronger. The cost increases. An object tube is divided into three stages of an accident, namely the pre-accident phase, the accident phase and the post-crash phase. Speed affordability cost The chunks of the object tube are separated and the acceleration cost is calculated for these fragments Of tube. As the vehicles collide, their direction changes. Change of direction In the post-accident phase, the strength is calculated using the change in cost of speed. Constant frame.

2. Rear-end Collision

A rear-end collision is a traffic collision where the vehicle crashes. Vehicle in front of it. The bounding box of each vehicle tube merges to form it Size prominence. The object tube trajectory merges and in this case the trajectory abruptly ends. Acceleration changes are seen in In some collisions, the speed and direction of the object changes.

3. Single-Vehicle Collision

A single-vehicle collision is a collision involving only one vehicle. In a single-vehicle collision, a vehicle changes its trajectory. a sudden The end of the trajectory of the object tube is observed. Acceleration changes This type of collision also appears.

4. Intersection Collision

A vehicle collision at road junctions is a common type of road collision. They are also called inter-collision collisions. It may be a head bump or rear-end collision. All properties of head-on or rear-end collision are present. Bump into in- tersection. This type of important research work [22] exists Collision.

A head-on collision may involve a head-on collision when a vehicle is crossed Opposite lane of traffic to turn at an intersection, or when passing through a side effect A vehicle crosses a nearby vehicle at intersections.

5. Severity Classification

The system examines the severity characteristics of un- usual events Intersections with the aid of video processing techniques and statistical deviation analysis Methods. Trajec- tory of normal vehicle speed, to detect unusual events The clustered and common root model is studied by Continuous Hidden Markov Sample. In the second part, abnormal ratio- temporal deviations are detected using maximum likelihood. As a next step, Definition and classification of severity is done for unusual events using k-nearest Nebula and support vector machines methods. Two-tier event classifier Designed to classify abnormal observations into one of low or high serious events Classes. The results indicate that unusual events can be detected and represented. Probability by probabilities, and depending on these probabilities, severity analysis Can be done successfully.

6. Motion Interaction Field

This is a new method for modeling interactions between multiple moving objects to detect traffic accidents. The method to model object interactions is Motivated by the motion of water waves reacting to moving objects on water Surface. The shape of the water surface is drawn as a sphere using Gaussian Kernel, referred to for the Motion Interaction Field (MIF). With good use The most symmetric properties of MIF, we can detect and localize traffic accidents, without solving complex vehicle tracking problems. Experimental results show that it The method improves existing functions in the detection and localization of traffic accidents.

A new field-based method for modeling interactions be- tween multiple moving objects for traffic accident detection and localization without effectively tracking the vehicle And complex learning processes. The proposed interaction model is inspired by Surface movement of water when multiple objects are moving over water. When a The object moves on water, it pushes water molecules and creates waves where, water The surface rises towards the front of the object and falls towards the back of the object. Such natural phenomena are formulated in the field using a Gaussian kernel that depends on both the speed and the direction of each moving object. We mention it Model as Motion Interaction Field (MIF). In addition, we develop a criterion Detect traffic accidents by viewing the MIF characteristics. Through experiments, it It is proved that, the method improves the state-of-the-art in detection and localization. Traffic accident in video stream.

7. Single-Vehicle Collision

Single-vehicle collision is a vehicle-only collision. In a single-vehicle collision, a vehicle changes its trajectory. Ac- cidental The end of the trajectory of the object tube is observed. Change in acceleration Also found in this type of confrontation.

V. CONCLUSION

In this paper, we demonstrate video summarization based event detection for road traffic surveillance videos. Depending on the salient features of the moving object, an optimal sum- marization framework is proposed in this paper. This frame- work is tested at various stages of road accidents. We also tested it for different types of collisions. Experimental results show that optimal summary based event detection provide a faster visualization of round the clock surveillance videos. Experiments have shown promising results and great potential for using video summarization to detect an event.

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