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Detection of Astonishing Accidents in Tunnel using Deep Learning Algorithm

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Abstract: Roads in tunnels vary in many ways from certain sections of open roads. For many drivers, the subway is an unusual driving area in a road network that can create even pressure. In conjunction with the Advanced Learning Network known as the Object Detection and Monitoring System, a quick and standard tracking system used for detecting automatically and unexpected incidents monitors on CV tunnels, Writing weight acquisition, (2) standings, (3) people outside the tunnel (4) fire. Odts accepts the video frames as input to obtain the location binding (BBox) result for object binding and compares BBoxes of current and previous video images to give each moving object a unique identification number. With this system, you can track a moving object over time, which is unfamiliar with the normal object detection settings. An in-depth learning model was developed in the ODTS with a series of graphically designed (AP) data sets of 0.8479, 0.7161, and 0.9085 values for direct, automatic, human, and product items, respectively. Subsequently, based on the in-depth learning model developed, the ODTS video risk assessment system was evaluated using four risk video recordings for each risk. This allows the system to detect all crashes in 10 sec. The ODTS acquisition capabilities can be automatically upgraded without changes to program codes if the training database is improved.

Keywords: Object Detection R-CNN, Object Tracking, Object Detection and Tracking system, Detection for Unexpected Events, Tunnel CCTV Accident Detection System.

I. Introduction

Object detection techniques are used systematically to determine the size and location of target objects from images or videos. Numerous applications have come up such as driving a car, cancer identification, CCTV surveillance and security etc. Objective is the part of image processing that must be done with a different identity to locate objects that have been identified over time. However, to track items, you need to set the item category and the standard image level provided for the first time the item is detected. Therefore, it can be said that the tracking results of an item must be accompanied by a large degree in the performance of the acquisition of object in question. The technology of object tracking has been successfully used to detect pedestrians and vehicles to monitor traffic cameras, to detect criminals and security in other affected areas, etc. In the field of automotive management, this article has conducted research and analysis to monitor traffic conditions by self-discovery.

According to [1], for self-driving cars a road vehicle detection system has been developed. With the help of Confusion Neural Network (CNN) the system detect object and classify based on the type. This algorithm tracks the object by dynamic tracking based the object position. The monitor then displays a local image of the vehicle with the object being viewed by the bird's eye and the system calculates the distance between the moving car and the displayed objects of the vehicle. It allows to estimate the location of the vehicle so that it supports automated driving systems. This allows for a vertical tolerance of 1.5 m for the vehicle object and a horizontal tolerance of 0.4 m for the camera.

In [2], in conjunction with CNN a deep learning-based sensing system was developed and also Support Vector Machine in order to monitoring vehicles operating on any roads. This captures CNN's satellite image function using image of satellite as input and it also performs SVM binary classifications to locate the BBM vehicle. In addition, Arnold, Pradana, Kurusinka [3] a system for estimating vehicle speed, classifying vehicle types, and analyzing traffic volume was developed. This uses bBox obtained with the help of searching for objects based on videos or images. Algorithms used in computers have been compared to Gaussian composition models - SVM and RCN faster. To identify more accurately the location and vehicle type by R-CNN. Finally, all are related to content discovery based monitoring systems for obtaining traffic information, showing exceptional performance in intensive learning. However, it is difficult to specify and track identifiable items as individual IDs, all with the same ID from time to time.

Therefore, it seeks to develop an ODTS that combines object learning tracking algorithm with intensive learning-based object recognition process to obtain moving information about target objects. Tunnel crash detection systems are also considered under ODTS [4.7]. It is used to detect or unexpected events when the object and target area are moved to CCTV.

II. Object Detection and Tracking System based on Deep Learning

A. Model

It is believed that ODTS is sufficiently trained to identify an object within a specific framework. ODTS receives the selected video frame over a period of time and wins the coordinate set, n BBoxs are found. During a trained object detection system, objects in a given frame are T.

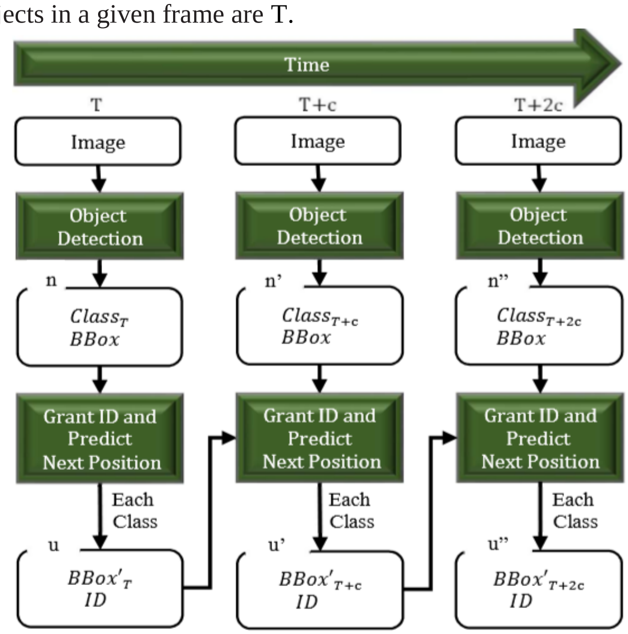

Fig. 1. Object Detection Tracking system over time

Then, based on the information about the found objects, a static object identification module is launched to assign a specific identification number to each known object and to estimate the next location of each object. The number of Bbox monitors varies from n. If previously found BBox 0, BBox's tracking number is equal to number of known objects. In other words, when there is no previous BBox detection, the current BBox detection class accepts the detected items. This object tracking module was created with the introduction of an object tracking algorithm called the SORT algorithm, [5] which uses the concept of intersection-on-union (IOU) to track a single object with a single identification number, and Kalman also uses Hungarian to predict the next location of detected objects.

T + c follows the same steps as T is the next step, through the newly given image and the same object detection module in C. Therefore, the IOU will be in all feasible pairs between positions removed from the position, the time at which T and the object in position will be found, at which T + c will be calculated. Closest objects that have highest IOU value are considered to be the same item with the same ID. Any element that does not contain a pair of objects with an IOU value greater than 0.3 of the class value ends with the area of interest (ROI).

Similarly, each item that does not contain a pair of items with an IOU value greater than 0.3 is considered to be newly released in T + c in RoI. The newly found object is affected by the new identification number, which does not overlap with the previous identification number. The system uses the fast RCNN learning algorithm [5] for object discovery and the ID identification mapping and SORT [6] for object tracking. SORT [6] allows tracking multiple objects at speeds of 100–300fps. The SORT [6] algorithm is used to track the system based on the IoU value, and capacity to follow objects is INFLUENCED by the video outline c [7] territory. The video outline rate can abbreviate the estimation time by changing the location scope of the object detection network. To verify this, it was possible to track objects within the experienced frame range, and then track objects up to a range of six frames. Increasing the frame range reduces the ability to track objects, so the range of video frame should be optimized for devices connecting to server.

B. Accident detection system in tunnel

In a avenue tunnel, driving is risky due to the fact there isn't sufficient area to clean from the everyday avenue, and ought to notify drivers of emergencies with inside the tunnel. In South Korea, individuals, fires, prohibitions and misconduct (WWD) are goal things and occasions that have to be monitored in country wide regulations. In South Korea: Korean national regulations require that individuals, fires, halt, and WWD be identified and monitored [4].

Meanwhile, target objects and unexpected untoward incidents are monitored in the tunnels by the CVC. And for this, an automated object recognition system with excellent performance is used outside the tunnels. However, the system does not work in a tunnel. The reason for this is: (1) The video tunnel has low lighting; video is well affected by rear light of a moving vehicle or light warning of moving car. (2) The tunnel tone of video is dark. As such, the outer tunnel path has a different color. Video surveillance structures evolved on roads out of doors the tunnels won't paintings well with inside the tunnel. Therefore, an automated twist of fate detection gadget that specialize in street tunneling is required.

To overcome this, a tunneling CCTV crash detection system was developed based on in-depth learning [7]. The intensive learning model from R-CNN was used for training. It is based on the model that teaches datasets of image where certain tunnel crashes occur. ODTS then only uses the feature of object tracking with the car object and tracking information for the target car object is periodically used to determine stop events using the car crash detection process.

First, the Area of interest on the CCTV screen is set in the tunnel and then change, distort the given image of the king from the original image of the CCTV to the culture. The process is similar to [1], but aims to reach a consistent for detecting system stops and

WWD. Then locate the person's auto, fire, and objects through a trained RCNN [5].

Additional "no fire" objects are defined directly by the object class to avoid incorrect detection of the fire object and to minimize the incorrect response to the fire object. No fire object will be provided for misleading items such as tunnel fire, car taillight. The classification of this data is reflected in the training, which generates differently defined object classes that are different from the background exception in the rapid R-CNN structure. In this method, detection of poor fire in untrained data can minimized.

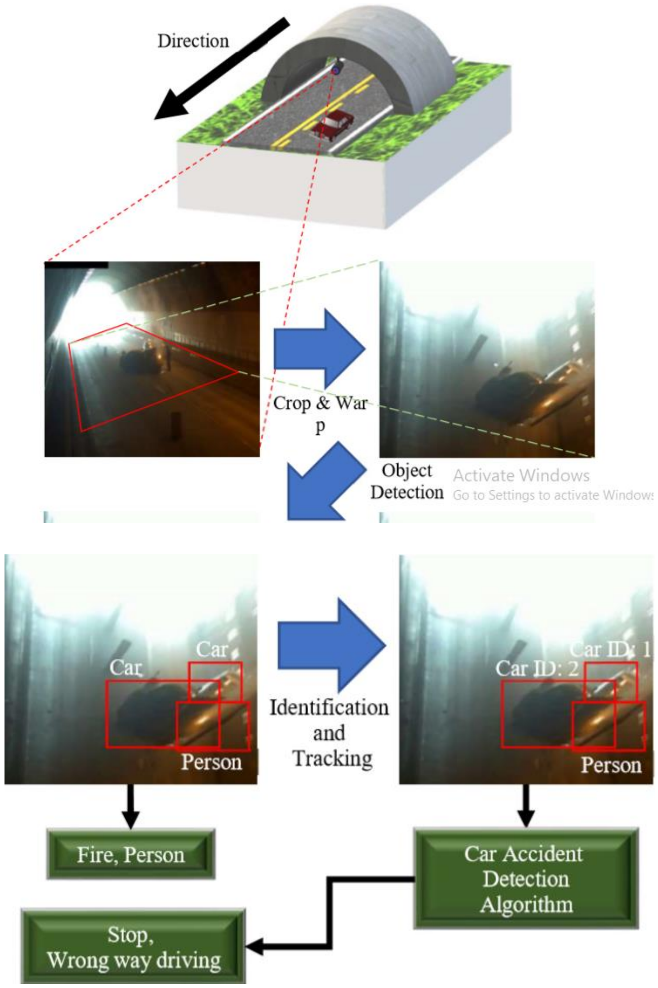

Fig. 2. Accident detection process using tunnel CCTV.

The automatic object is calculated using an algorithm of object tracking and also previous BBox of the same identifier is compare with the current BBox at the default point interval with each BB. At that point the WWD was determined by the intersection of the line (IoL), and the stop value was determined with the help of the IoU. a concept of IOU, line ratios equivalent to IoU. It uses only the BBox vertical value of to determine the value of inverse.

$$\text{IoL} = \frac{\textit{Overlapped Length of Vertical element of BBox}}{\textit{Union Length of Vertical element of BBox}}$$

The WWD standard is based on the CCTV image of a deformed tunnel to identify the movement of the BBox in vertical on the image. If the IoL value is less than the value of 0.75 and the direction of the column is opposite, it has been proven to be the opposite.

To determine the stop value of event they use criterion, because regardless of the address, the position and size of the bbqs must be taken into account. If it is 0.9 or higher, it appears to be a decision. Through the above process, tunnel video CCTV video systems are implemented for use with images of real objects and videos observed from tunnel sites.

III. Experiments

The two parts of system: performance measurement of intensive learning another one is system-wide crash performance of detection. I'm curious about how ODTS object recognition performance is heavily influenced. Therefore, the entire system requires Discovery's high-quality Object doctrine, thanks to the good practice of the Learning Object Discovery Network.

At that point, in light of the subsequent intensive learning model, the whole framework was tried to check whether it could distinguish each of the four objective mishaps. For this situation, because of the article recognition execution of the intensive learning model and the oppressive prerequisite of CADA, the framework was tried for each picture to decide whether it was conceivable to distinguish each condition.

C. Deep learning

The deep learning network was not comprised of video, yet a progression of still pictures. It defines the training cycle process through an epoch to entire dataset. The dataset to be learned contains pictures in case of accidents. R-CNN CNN has been used for rapid training [5].

Table-I. Image Dataset status

Number of Videos	**No of images**	**No.of. Objects**		
		CAR	***PERSON***	***FIRE***
45	70914	427554	857	44862

This dataset contains 70,914 multiple video images, and dividing the 45 videos into images. It is different from the whole in-depth learning process, there is no difference in teaching and inference data in the in-depth learning process. This is because the dataset used in this document, unlike the publicly available dataset, contains images in each video continuously. In other words, the images in every file has the similar image background and are different depending on the presence of objects. If training and tracking data is distributed for each image, the object's search network results screen will show similar performance. On other side, the stability of object detection throughout the video deteriorates, adversely affecting crash detection performance, making it difficult to test the entire tunnel-CCTV detection system's detection process for image crashes. Consequently, training is provided by collecting all available data and using data that evaluates the performance of an in-depth learning object search.

The number of fire items is very small as fire incidents are very rare in the tunnel. Accordingly, there is a high likelihood of distinguishing bogus location and fire, and what is significant at the passage control focus is that the bogus identification should be less lost discovery.

Systems reliability can be significantly compromised if systems installed in the field are often misidentified and misidentified. However, in the event that no data is found, detection performance can be automatically improved with the entire dataset within the time period mentioned in training dataset.

The fastest R-CNN training are performed by 10 eras. The R-CNN training team uses the Nvidia GTX 1070 for faster.

Table- II: Inference Dataset Result

No. of images	**Average Precision(AP)**		
	car	***person***	***fire***
70915	0.8478	0.7162	0.9086

The cope with of the AP values of the 3 goal gadgets. In the schooling dataset, the range of gadgets is the biggest item for vehicles and has a miles better AP cost for the automobile item than for different classes. In other words, the performance of the car's deep object detection in the video should be very reliable. The AP for an individual object has a relatively small value because the individual object has a smaller, longer, smaller size.

The use of fire extinguishing equipment is as high as 0.9085, but it is possible to misinterpret the material because the amount of material available for training is very low, 857. However, intensive training, including fire extinguishing equipment. This can be misleading. Be that as it may, to recognize the nearness of fire in the passage control focus, additional images of the fire must be collected and added to the structure.

D. Test for Accident detection

Performance in risk identification should be evaluated based on a trained in-depth learning model and in-depth learning tunnel hazards.

Video frame rate is 30 fps at 6 frames per second and should be detected within 10 seconds of visual inspection. The duration of the video, the action time and the detection time are shown in Table III.

Table- III: Time of each accident detected by the accident detection system

Accident video information	**Video time element**		
	Video Length	***Occurrence Time***	***Detected Time***
Stop	126s	5s	7s
Wrong Way Driving	29s	4s	12s
Fire	64s	29s	29s
Person	72s	50s	50s

As is a feature of each, it has been found to be 2.4 cycles per second in our experience. However, this configuration was able to stop a difference between 2 seconds and 8 seconds for WWD detect. On the other hand, the images were soon visible in the images, including personality and fire, immediately after the accident. However, there is a limitation that the images used in Table 3 are the ones used for training, so that they differ from the context installed directly in the field. Therefore, the review requires a review bank and a request for additional videos.

IV. Conclusion

A new ODTS process by connecting the Deep Learning Object Discovery Network to an object tracking algorithm and shows that dynamic information can be retrieved and used for a specific object class. On the other side, the sorting used during object tracking is important due to material detection performance, odts uses only living box information, not an image. Therefore, the performance of continuous material discovery can be low if the object recognition method does not depend on the relative performance of object discovery.

Training and evaluation were conducted to identify and identify in-depth learning aspects from the system-wide crash. This system combines everything that discriminates in each wheel based on the changing information about the objects in the car. After the imaging test on each lock, it can able to detect accidents in 10 secs.

Deep training ensures the effectiveness of material detection of a reliable material and shows relatively low material recognition performance. However, in case of fire, there is a risk of misdiagnosis in untrained videos as there are not enough fire components. However, the wrong detection can be reduced by creating fire retardant objects. Deep learning material detection network fire material detection performance should be improved by protecting fire image. Odts can be portrayed for instance of a system for detecting video surveillance accidents in subways, be that as it may, can likewise be utilized to follow the dynamic movement of a specific article, for example, vehicle speed appraisal or illicit leaving checking. To build the dependability of the framework, it is important to store a few pictures and ensure against fire and individual items. In addition, tunnel maintenance improves the reliability of site application and continuous monitoring systems.

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