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DEEP LEARNING-BASED TRAFFIC ACCIDENT DETECTION USING CCTV MONITORING

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Abstract: *There are many studies on the prevention or detection of vehicle accidents. Most of them include detectors that can cause accidents or information about accidents. On this note, the system that detects accidents can be studied. The machine will collect the necessary records from nearby cars and process the facts, gaining knowledge of the tools to find viable injuries. Machine recognition algorithms have successfully distinguished between strange and normal behaviour. This test looks for activities to investigate traffic behaviour and recall vehicles that move more than the behaviour of recent-generation site visitors as a possible match. The results confirmed that the clustering algorithms could effectively detect accidents. This system makes it possible to adjust a moving object in time, which is not usually done in traditional object detection frameworks. The ODTS deep learning model was tested on the tunnel event image dataset with Average Precision (AP) values of 0.8479, zero, 7161, and 0.9085 for the target items: vehicle, person, and fire, respectively. Then, based on the expert deep field model, the ODTS-based CCTV incident detection system was examined using four incident films, along with each incident. As a result, the system can detect all infections within 10 seconds.*

Keywords: *Traffic accidents, CCTV Accident Detection System, deep learning, Object Detection.*

I. INTRODUCTION

Traffic accidents disrupt the operations of site visitors, damage the flotation of site visitors, and cause excessive urban problems globally. Significant visitor injuries can cause irreparable damage, accidents, and even deaths from time

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to time. The National Highway Traffic Safety Administration (NHTSA), which publishes annual visitor safety reports, states that in 1988 there were more than five million motor vehicle accidents in states, and about 30% of them caused fatalities and accidents (NHTSA, 2015). After years of studies, it has been widely demonstrated that it can achieve significant reductions in the impact of an accident through effective detection strategies and corresponding interaction techniques. As a vital part of traffic accident control, correct and rapid detection of site visitor accidents is essential to modern transportation management (He et al., 2013). Conventional detector-based methods usually give an accurate match for the location and time of visitors and are valid in many packages (Hall et al., 1993; Samant and Adeli, 2000; Sethi et al., 1995). Despite modifications from previous research, traditional screening methods using the simplest information from site visitors still encounter positive demanding situations. First, most of the previous research, which applied sphere records to determine traffic injuries, is based on the assumption that the statistics are reliable. However, detector errors and verbal interchange errors are permanent problems in the operations of site visitors. For example, the Illinois Department of Transportation (IDOT) in Chicago has said that about five percent of its loops (detectors) are down at any given time (Kell et al., 1990). Defecting sensors should cause even greater problems in detecting matches over large areas. Second, the uncertain nature of visitor patterns and non-recurring events may also undermine the ability of visitor metrics to account for visitor incidents. In addition to site visitor accidents,

it can also disrupt daily visitor operations with the help of other elements, such as parades, road construction, race walks, etc. Therefore, visitor flow and occupancy metrics inherently serve as a diagonal aid to accident traffic rather than a direct test. There are efforts to use clustering or classification methodologies, including the K approach (Münz et al., 2007), in large fact sets to reduce errors to meet these challenges.

The object detection technique has been effectively implemented to determine the size and function of target objects created in images or movies. Various applications have emerged mainly in car self-driving, CCTV monitoring, protection system, cancer detection, etc. Observation of the object is another position in image processing that is achieved with a specific identity and tracking the locations of specific objects over the years. However, for song objects, it is important first to determine the element's class and position in a given still image first through object detection. Therefore, it can say that the results of object monitoring should be highly dependent on the detection performance of the object in question. This era of item tracking has been successfully applied to track targeted pedestrians and moving vehicles, track accidents on the site visitor's camera, track thieves, and protect positive neighbourhood landmarks. On the site, visitors manipulate the field; a case study on the analysis and manipulation of traffic situations through the detection of computerized objects is presented in this article. Abstracts are given as follows. According to [1], the road vehicle detection device is developed for self-use. This system detects the vehicle body and classifies the vehicle type through a Convolutional Neural Network (CNN). The vehicle object tracking rule set tracks the vehicle object by shifting the average tracking factor according to the location of the vehicle element diagnosed in the image. Then, the display suggests a local image, such as a bird's eye view, with the vehicle elements displayed. The system computes the distance between the traveling vehicle and the displayed vehicle elements. This device operation allows an objective view of the position of the vehicle's body so that it can assist with the help of the autonomous drive system. As a result, it can locate the vehicle element within a vertical tolerance of 1.5m, horizontal zero, and 4m on the digital camera.

II. BACKGROUND WORK

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Recently, automatic incident detection has attracted much attention in freeway control systems to reduce traffic delay, advance road safety, capacity and real time traffic control because when freeway and arterial incidents occur, they cause congestion and mobility loss, if they are not fixed immediately, they can cause second traffic accidents. Algorithms which is used to detect incidents include the pattern recognition techniques , time series(Angshuman, 2004), filtering, fuzzy set(Edmond Chin-Ping Chang and Kunhuang Huarng, 1993), and artificial neural network(Edmond Chin-Ping Chang, 1992) (Wang et al., 2007) Unlike sensors, vehicles can be equipped with sensing devices with high processing power, high cost and weight like GPS, chemical spill detectors, video cameras, vibration sensors, acoustic detectors, etc.. since they are not usually restricted by energy and size constraints. VANETs deployment scenario is different than traditional wireless sensor network deployment scenarios since vehicles expose limited mobility pattern due to street shapes, intersections, speed limitation, vehicle size. If vehicles are equipped with network cards, they can access wireless access networks like DSRC/WAVE, Cellular, Wifi, WiMAX, etc. (Lee and Gerla, 2010).

In [2], another deep learning detection system based on deep mastery was developed jointly with CNN and the Support Vector Machine (SVM) to detect vehicles moving on city streets or highways by satellite. This system extracts the satellite image function through CNN using the satellite image as the access fee and reproduces the binary class using SVM to find the BBox car. Furthermore, Arinaldi, Pradana, and Gurusinga [3] have developed a device for estimating vehicle speed, classifying vehicle types, and examining the volume of site visitors. This tool uses BBox obtained by detecting items based on images or gifs. The algorithm applied to the device has been changed compared to the faster Gaussian mixture model + SVM and RCNN. Then it appears that the faster R-CNN could more accurately detect the location and type

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of vehicle. In other words, the deep knowledge-based object detection method can be said to be developed into a set of rule-based object detection machines. In conclusion, all the optimization cases in this document are based on the monitoring device based on address object detection to harvest traffic logs, showing exceptional performance with the deep study. However, it was difficult for all of them to assign specific identifiers to the discovered items and assign them to music while maintaining the same identifier over the years.

Automatic accident detection has recently attracted a lot of attention in highway handling systems to reduce traffic delays and improve street protection, capacity, and real-time traffic control because accidents occur on highways and arterial roads; they cause congestion and loss of movement, if possible. Unsteady without delay could be the cause of second traffic injuries. Algorithms used for accident detection consist of the techniques of sample reputation, time series (Angshuman, 2004), filtering, fuzziness array (Edmond Chin-Ping Chang, 1992) (Wang et al., 2007). Unlike sensors, cars can be equipped with high processing power, high value, and weight detection devices such as GPS, chemical spill detectors, video cameras, vibration, acoustic detectors, etc. It can no longer be restricted naturally due to power and length limitations. The VANET deployment scenario is unique to traditional wireless sensor community deployment scenarios, where vehicles reveal a navigation pattern restricted by street shapes, intersections, and the vehicle speed and length dilemma. If cars are equipped with community cards, they can access wifi networks such as DSRC/WAVE, Cellular, wifi, WiMAX, and many more ((Lee and Gerla, 2010).

Traffic Flow/ Incident Detection

Advances in intelligent transportation systems require more accurate movement data, and providing this data has become a huge task for public institutions and private

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companies. Unfortunately, conventional traffic sensors used to measure modern traffic situations, such as loop detectors, are useless in providing the correct information about the popularity of site visitors in the street community.

Traffic-related records from other assets, including cameras, GPS, mobile smartphone tracking, and sonar engines, are used to improve the accuracy of traditional scaling structures. Traffic control management centers also keep this visitor data for future use. Data merging techniques can be used to blend offline visitor and multi-resource records to produce better insights into the status of visitors to highway sites and the future development of critical roads (Faouzi et al., 2011). Schaffer, Bayesian inference, and logical voting. Most of these strategies combined vehicle test data with traditional visitor data for accident detection. The neural community approach has been widely used to detect accidents of detected files. (Faouzi et al., 2011).

III. DEEP LEARNING-BASED OBJECT DETECTION SYSTEM

Recently, object detection has become one of the powerful and popular features in the imagination and insight laptop to process many packages, such as clinical image processing for breast cancer, skin cancer, brain accidents, blood cells, and more. In addition, it is used in monitoring stations for real-time monitoring to detect crowds and anomalies.

The traditional object detection methods are not real-time due to the long processing time. Moreover, the accuracy does not always reach the level required for implementing practical programs. Non-object-detection neural networks require first feature extraction via techniques such as the Viola-Jones object detection framework, which is entirely based on Haar features and Scale-Invariant Feature Transform (SIFT) directed gradient graph (HOG) functions followed by an SVM classifier by class. Extensive procedures based on deep data have solved these useless feature engineering steps using Convolutional Neural Networks (CNN) for image processing. CNN extracts feature by routinely training and updating community parameters without human intervention at an accelerated pace, accuracy, and overall performance.

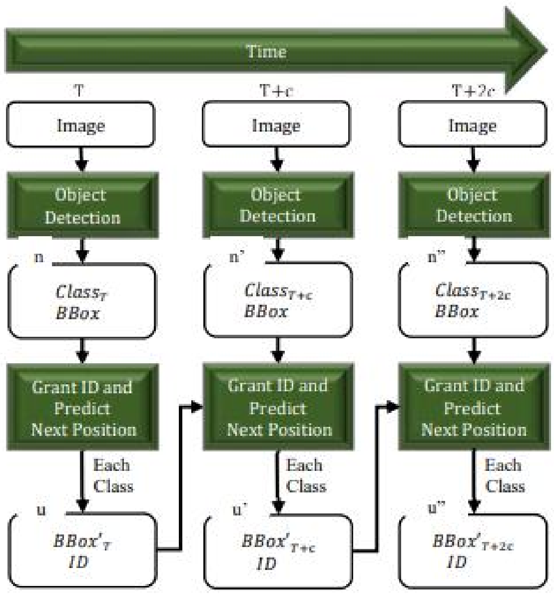

Fig.1 Object detection and tracking process of Object Detection Tracking system over time

Figure 1 shows the material detection and tracking system through ODTS over the years. ODTS is assumed to be skilled enough to perform object detection on a given image body correctly. ODTS receives selected video frames in one program language period c for one-time period c and gain format units, n BBoxes are detected. BBoxT devices on the image body set at time T, from the expert element detection device. The corresponding type or $Class_T$ each detected object BBo_T classified by the object detection module.

Then, based on the statistics of the detected object, a child element tracking module began to assign a wide range of micro-identifiers to each of the detected objects, IDx, and predict the next function of each device, BBoxT' BBox monitoring range u is not like n. But if the traced BBox's bypass is 0, then the wide range of BBox monitoring is equal to the number of detected items. For example, at time T + c, if u is zero, then u is "equal to n." In other words, in the absence of the old BBox tracking system, the modern BBox tracking system grabs the detected items according to each magnificence. This element tracking unit is configured by introducing a set of elements tracking rules called the SORT algorithm [5], which uses the idea of an

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Intersection-Over-Union (IOU) to allude to the same object with the same set of identifiers and, in addition, uses Kalman and Hungarian ellipses. A set of rules for predicting the subsequent function of a detected object.

This system uses a faster RCNN scan algorithm to detect elements and SORT to challenge element identification and tracking. SORT is understood to allow multiple objects to be tracked using a rate of 100 frames per second. Machine strategies track these elements using the SORT algorithm based on the IoU cost, reducing the element tracking ability with video frame interval. The language period of the video c-frame software can reduce the amount of computation over time with the help of modifying the language of the article detection network detection software. The object observing ability was tested during the c-program language period, and then it became possible to sing the objects up to the six-frame c-program period. However, the advent of the framework programming language significantly reduces the ability to monitor objects, so the video body programming language must be optimized for the number of digital camera devices simultaneously connected to a deep learning server.

Tunnel accident detection system

Driving in a street tunnel is risky as it is an unsuitable area to evacuate for miles compared to a known highway, and you must notify drivers in the event of an emergency in the tunnel [7]. Therefore, in South Korea, People, Fire, Stop, and Wrong Drive (WWD) are the target devices and events that must monitor within the framework of national law [4]. Driving in a street tunnel is risky as it is not enough space to evacuate compared to a luxury highway. Therefore, drivers should be informed when an emergency occurs inside the tunnel [7]. In South Korea, devices or activities must be detected and monitored: Person, Fire, Shutdown, and WWD by Korean national regulations.

Meanwhile, target items and surprise activities are tracked through CCTV in

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the tunnels. It can adapt the automatic object detection system for targets for the great performance of outdoor tunnels. However, the system does not work at all in a tunnel. This is because: (1) The video is dimly lit in the tunnel, so the video is highly animated by a vehicle taillight or a running vehicle warning light. (2) Tunnel video tone turned dark. In other words, it is different than the outdoor tunnel road. Due to the above reasons, it is possible that the video tracking system developed on the open roads of the tunnels will not work properly inside the tunnel. Therefore, a specialized automatic deflection detection machine is required in street tunnels. A tunnel CCTV accident detection system has been developed based on an in-depth study to overcome the above-mentioned problems. A deep mastering version of Faster R-CNN was used for instruction. This version was based on a version that learns photographic data sets that include some tunnel injuries. Then, the ODTS takes advantage of the element monitoring function most suitable for the vehicle element. The target vehicle element monitoring records identify stop and WWD occasions by periodically using the detection algorithm. Car accidents (CADA).

IV. EXPERIMENTS

Experiments with the machine developed in this test are divided into parts: the overall dimension of the study performed for the deep study and the corresponding performance of the whole machine. SORT used in ODTS suffers greatly from object popularity performance. Therefore, a general over-performance of object discovery is required to complete this device through appropriate learning of the deep knowledge object discovery community. Then, based on the deep understanding of the trained model, the entire system was checked to see if it could detect the four focused events of fate evolution. In this example, since both the overall performance of object detection for the deep learning model and the discriminative capabilities of CADA was required, the machine scans

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for each image to determine whether or not each scenario can be identified.

Deep learning training

Training in deep learning networks was not conducted by video but by a series of images. This document defines a single training method cycle for an entire data set during an epoch. The dataset to be discovered includes the images from the match events. R-CNN [5] uses the fastest training.

Table.1

Number of Videos	Number of images	Number of objects		
		Car	*Fire*	*Person*
45	70914	427554	857	44862

Table 1 suggests the popularity of the data set used in education. This data set consists of 70,914 video frames splitting 45 motion pictures into frames. In contrast to the well-known form of deep learning, real-world learning and inference information are no longer separated in the deep learning style. This is because, unlike publicly available data sets, the data set used in this document is that the images are continuous in each video. In other words, the images in each video report have the same image history and fluctuate based on the presence of the elements. Therefore, if the education data and inference facts of each image are divided, the overall inference performance of the object discovery network can show a similar overall performance. On the other hand, the stability of object detection in the whole video may deteriorate, which negatively affects the overall performance of the match detection, so it is difficult to fully test the detection technology of the match detector. CCTV photos of the tunnel.

V. CONCLUSION

This paper proposes a new approach to ODTS by combining a deep knowledge-based object detection network with an object control rule set. It indicates that dynamic registrations of an object can be received and applied to the magnificence of a specific object. On the other hand, object detection performance is critical because the SORT used in ODTS object monitoring uses simpler BBox information without an image.

Therefore, the performance of continuous object detection may be less desirable, except that the object monitoring algorithm is highly dependent on the overall performance of the object's popularity. And the ODTS-based tunnel CCTV incident detection system has become advanced. Experiments were carried out on school education, assessing the object detection community's deep knowledge and revealing the entire system's conformity. This device aggregates each cycle characterizing each cycle based on the dynamic stats of the vehicle's hardware. As a result of experimenting with the image contained in each accident, it was possible to detect injuries within 10 seconds.

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