

AN IMPLEMENTATION METHOD OF REAL LEARNING FOR THE AUTOMATION IDENTIFICATION OF UNEXPECTED INCIDENTS IN TUNNELS WITH SUBPAR CCTV MONITORING CONDITIONS

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ABSTRACT: The ODTS, or Identifying Objects & Tracker System is coupled utilising a renowned deep learning network called Faster Region Convolutional Neural Net (RCNN). For both traditional object detection and monitoring, an algorithm is shown. and used to automatically detect and monitor unexpected events on CCTVs. These unexpected events may include fire, people exiting the vehicle, or wrong-way driving or stopping. In order to acquire Bounding Box (BBox) results by detecting objects, the ODTS takes in video frames in real time. It then evaluates and contrasts The footage includes images from the past and present Bounding Boxes. to provide every moving and found object a distinct ID. This method makes it possible to track any moving item in time, which is uncommon in traditional object detection frameworks. A collection of event data from the tunnels was used to train a deep learning model with the aid of ODTS, yielding (AP) Person, Car, and Fire have corresponding to mean accuracy scores of 0.72, which is 0.85, and 0.91. Images of events in the tunnels were used to train a model based on deep learning in the Object Detection Tracking System (ODTS) to (AP) Average Precision values of 0.7161 for Person, 0.8479 for Car, and 0.9085 for Fire. CCTV is a surveillance accident detection system based on ODTS in the tunnel was evaluated using a deep learning model that was built using four accident movies. All of the incidents were recognised by the system at 10-second intervals. It is significant to highlight that since the training dataset will grow rich, The ability to detect accidents might be automatically increased without requiring any changes to the source code.

Keywords: CCTV system for detecting accidents and objects and tracking system, faster RCNN for object tracking algorithms and object detection, and unexpected event detection.

I. INTRODUCTION: Object detection technology may be used to determine the size and location of target items that appear in photos or movies. Numerous applications have emerged for CCTV surveillance, security systems, cancer diagnosis, and mostly self-driving cars. Determining the object class and location in a static picture using object detection is crucial for object tracking. It may be inferred that object detection performance should have a significant impact on object tracking outcomes.

Tracing people and moving cars, keeping an eye on accidents via traffic cameras, keeping an eye on crime and security in communities of interest, and more are all made possible by this technology. In this research, a case investigation on analysis and traffic situation management has been conducted using autonomous object identification.

The creation of a self-driving automobile was started using a technology for detecting vehicles on the road. CNN detects things in vehicles and categorises the kind of vehicle. The algorithm for tracking of the identified vehicle item will track the vehicle object, and the tracking centre point is adjusted based on the object's location on the picture. Similar to a bird's-eye perspective on a vehicle object on the monitor, the system determines the separation between the visualised vehicle item and the driving automobile.

The procedure used by this system helps to see the location of the vehicle item in order for it to support the self-driving system. The margin of error at the camera is localised, and the vehicle object is 0.4 meters horizontal and 1.5 meters vertical. An additional detection mechanism based on deep learning that uses CNN and Support Vector Machine, or SVM, was created. to track cars travelling on roads or highway with the use of satellites. The system uses CNN to extract the feature from the satellite picture, and then uses Support Vector Machine for binary classification in order to determine the vehicle's Bounding Box.

This system uses Bounding Boxes, which are created by detecting objects based on photos or videos and algorithms, in contrast to the Gaussian mix model Support Vector Machine (SVM) and the quicker RCNN. The kind and location of the vehicle were found to be more reliably detected by the quicker R-CNN. Therefore, it may be argued that the algorithm-based approach to object detection is inferior to the deep learning-based strategy.

Thus, it can be inferred that every development case in this work deals with object information, demonstrating exceptional performance via the use of deep learning. Therefore, this research attempts to develop an object detecting along with tracking device (ODTS) that can gather data on movement target objects by fusing An object identification with deep learning process using an object tracking technique.

II. LITERATURE SURVEY

[Paper 1: An aerial view identifies the location of nearby automobiles..](#)

Using geometries and stereo vision, a novel framework for vehicle recognition and localisation with partial representations is put forward. We develop a tracking technique that recognises all cars that are partly visible. This method detects the edge of a vehicle on the ground in order to track partly visible cars. Grounded edge detection is the process of identifying a vehicle's edge on the ground. A point of reference is then chosen for the Kalman filter's tracking. This suggested method effectively enables the tracking and identification of partly visible vehicles.

[Paper 2: Combining exemplar classifications with complex features for robust auto recognition.](#)

The potential use of deep neural properties for reliable vehicle identification is investigated in this work. In order to recognise vehicles in satellite-provided photos, an identification framework for vehicles is thought to combine a strong instance classifiers according to Exemplar SVMs, or E-SVMS, which use the DNN (Fully Convolutional Neural Network)-based feature learning technique. Differential picture characteristics, which have an excellent capacity for learning, are learnt using DNN.

[Paper 3: Vehicle identification and categorisation for traffic video analysis.](#)

This research describes a traffic video analysis system. This system makes use of computer vision methods. The technology is specifically designed to automatically gather crucial data in a computerised format for regulators and policymakers. These data include video, lane use monitoring, vehicle speed estimate, vehicle type categorisation, and vehicle counting. This system's primary function is to identify and categorise cars seen in traffic recordings. For this objective, two models are used.

1. A system based on MoG and SVM

2. A quicker method based on RCNN

Paper 4: Self-Supervised Online Multi-Instance Innovative Object Segmentation is the topic of Paper 4.

Using just a monocular camera placed on a vehicle and no prior information of the object's shape, position, or visual appearance, this research develops a method for continually distinguishing moving objects. Our system can identify moving objects without prior information of their visual existence, position, or shape, which sets it apart from conventional tracking-by-detection-based systems. Furthermore, the classifier is used to produce labels from previous frames of the same item, enhancing the ongoing observation of particular objects that rely on motion.

III. SYSTEM ANALYSIS

EXISTING SYSTEM

Using a CNN (Convolutional Neural Network), the current system will identify the vehicle object and categorise the sort of vehicle it is. The object's tracking algorithm detects the vehicle object and adjusts the tracking centre point based on the location of the recognised vehicle. The monitor will then display the localised picture, which resembles a bird's-eye perspective, coupled with the vehicle's visualised items. The distance that exists between the driving automobile and the vehicle item will also be determined by the system.

Disadvantages: - Using the satellite picture as input, this system leverages the CNN characteristic of satellite images. In order to identify the vehicle-BBox, Binary Classification is used in conjunction with SVM based on input data. This technique makes use of the bounding box that is produced by detecting items on pictures or videos.

THE SUGGESTED SYSTEM

By merging the object tracker method with the deep study-based object identification method, the suggested system aims to provide an object detecting & Yolo's tracking system (ODTS) might gather movement data about target objects with their names. It is assumed that ODTS has received sufficient training to perform object detection on appropriately allocated picture frames. ODTS detects BBoxes by sensing certain video frames at a chosen time interval c and obtaining centroid sets. BBox t of items from the trained object detection system on a picture of the present item at t . The detection of objects module continuously classifies each observed item BBox t according to its matching type or class Class. YOLO Model and R-CNN (Regional Convolution Neural Network) are the algorithms.

ADVANTAGES

1. The Yolo object identification model was trained using an R-CNN deep learning model.
2. The Yolo object tracking model was developed in order to construct this object tracking module.
3. As a result, the system will identify objects more quickly.

IV SCREEN SHOTS

```
C:\Windows\System32\cmd.exe - python cctv_video.py --input test.mp4 --yolo yolo-coco
Box[15]: 614 383 64 60 Labels[15]: car classIDs[15]: 2 AveragePrecision[15]: 0.9708886742591858
Box[14]: 384 321 73 56 Labels[14]: car classIDs[14]: 2 AveragePrecision[14]: 0.963583767414093
Box[11]: 630 217 30 20 Labels[11]: car classIDs[11]: 2 AveragePrecision[11]: 0.9064033409154114
Box[2]: 1005 415 132 118 Labels[2]: truck classIDs[2]: 7 AveragePrecision[2]: 0.8711925745010376
Box[10]: 520 212 33 27 Labels[10]: car classIDs[10]: 2 AveragePrecision[10]: 0.804618239402771
Box[8]: 604 166 20 21 Labels[8]: car classIDs[8]: 2 AveragePrecision[8]: 0.8008059127807617
Box[7]: 639 149 20 18 Labels[7]: car classIDs[7]: 2 AveragePrecision[7]: 0.76325923204422
Box[6]: 637 137 22 18 Labels[6]: car classIDs[6]: 2 AveragePrecision[6]: 0.7327922582626343
Box[5]: 547 135 17 13 Labels[5]: car classIDs[5]: 2 AveragePrecision[5]: 0.7062139091491699
Box[4]: 586 101 19 11 Labels[4]: car classIDs[4]: 2 AveragePrecision[4]: 0.5455284118652244
Box[9]: 448 216 32 26 Labels[9]: car classIDs[9]: 2 AveragePrecision[9]: 0.5142262578010559
Complete time for algorithm 4.112649440765381
Frame No: 46
Box[3]: 457 495 111 98 Labels[3]: car classIDs[3]: 2 AveragePrecision[3]: 0.9819610714912415
Box[13]: 593 312 49 53 Labels[13]: car classIDs[13]: 2 AveragePrecision[13]: 0.978967010974884
Box[12]: 450 313 103 52 Labels[12]: car classIDs[12]: 2 AveragePrecision[12]: 0.9677761793136597
Box[14]: 385 320 70 50 Labels[14]: car classIDs[14]: 2 AveragePrecision[14]: 0.9627906084000669
Box[15]: 609 386 74 64 Labels[15]: car classIDs[15]: 2 AveragePrecision[15]: 0.9615384936332703
Box[2]: 996 404 133 116 Labels[2]: truck classIDs[2]: 7 AveragePrecision[2]: 0.9123777747154236
Box[11]: 630 213 30 23 Labels[11]: car classIDs[11]: 2 AveragePrecision[11]: 0.8713926076889038
Box[10]: 520 210 36 31 Labels[10]: car classIDs[10]: 2 AveragePrecision[10]: 0.8163345456123352
Box[5]: 544 135 19 14 Labels[5]: car classIDs[5]: 2 AveragePrecision[5]: 0.8006945252418518
Box[8]: 605 165 28 19 Labels[8]: car classIDs[8]: 2 AveragePrecision[8]: 0.7980472445487976
Box[7]: 639 149 19 17 Labels[7]: car classIDs[7]: 2 AveragePrecision[7]: 0.7330524325370789
Box[6]: 638 134 22 20 Labels[6]: car classIDs[6]: 2 AveragePrecision[6]: 0.674657040864563
Box[9]: 445 216 35 26 Labels[9]: car classIDs[9]: 2 AveragePrecision[9]: 0.6428461074829102
Box[4]: 584 101 19 11 Labels[4]: car classIDs[4]: 2 AveragePrecision[4]: 0.5080229640007019
Complete time for algorithm 4.166612140284912
Frame No: 47
[INFO] cleaning up...
[Msg] Accidents frames analysed
[INFO] Wrong Driving Analysis Started
extracting frames from image
Reading and resizing the first image
Shape of first image: (200, 400)
Minimum Intensity: 0
Maximum Intensity: 255
```



V.CONCLUSION

As a result, we attempted to apply the paper by Kyu Beom Lee and Hyu Soung Shin, "An Implementation Of a Deep Learning Model For Automatic Detection Of Unusual Events During Poor Conditions for CCTV Monitoring in Tunnels," which was presented at the 2019 IEEE Internationally Conference of Deeply Learning And Machine Learning. This study presents a novel ODTS technique that learns and uses dynamic data about an item for a certain object class by combining an object tracking algorithm with a deep learning-based object identification network. Since SORT, which is used in ODTS tracking of objects, relies mostly on BBox data and does not use an image, the object recognition performance is crucial. Therefore, continuous performance of object detection may not be required Unless the tracking object approach is highly based on the effectiveness of object recognition. Additionally, a CCTV in tunnels Incident An ODTS-based detection system was created. Tests were conducted on the identification of an across the system accident and the instruction and assessment of an object for deep learning recognition network. The algorithm's total time is 4.166. For each box found in the frame, the average accuracy is computed. The algorithm detects 47 frames in all.. The range of average accuracy is 0.5 to 0. The intensity ranges from 0 at the least to 255 at the greatest.

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