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AUTOMATIC DETECTION OF UNEXPECTED ACCIDENTS UNDER CCTV MONITORING

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ABSTRACT

In this project, Object Detection and Tracking System (ODTS) in combination with a wellknown deep learning network, Faster Regional Convolution Neural Network (Faster R-CNN),for Object Detection and Conventional Object Tracking algorithm will be introduced and
applied for automatic detection and monitoring of unexpected events on CCTVs in tunnels,which are likely to (1) Wrong-Way Driving (WWD), (2) Stop, (3) Person out of vehicle intunnel (4) Fire. ODTS accepts a video frame in time as an input to obtain Bounding Box (BBox)results by Object Detection and compares the BBoxs of the current and previous video framesto assign a unique ID number to each moving and detected object. This system makes it possible to track a moving object in time, which is not usual to be achieved in conventional object detection frameworks. A deep learning model in ODTS was trained with a dataset of event images in tunnels to Average Precision (AP) values of 0.8479, 0.7161 and 0.9085 for target objects: Car, Person, and Fire, respectively. Then, based on trained deep learning model, the ODTS based Tunnel CCTV Accident Detection System was tested using four accident videos which including each accident. As a result, the system can detect all accidents within 10 seconds. The more important point is that the detection capacity of ODTS could be enhanced automatically without any changes in the program codes as the training dataset becomes rich.

I.INTRODUCTION

Object detection technology has been successfully applied to find the size and position of target objects appearing on images or videos. Several applications have appeared mainly in self-driving of vehicles, CCTV monitoring and security system, cancer detection, etc. Object tracking is another area in image processing to be achieved by unique identification and tracking the positions of identified objects over time. However, to track objects, it is necessary to define object class and position first in a firstly given static image by object detection. Therefore, it can be said that the results of object tracking should be deeply dependent on the performance of the object detection involved. This object tracking technology has been successfully utilized for tracing of targeted pedestrian and the moving vehicle, accident monitoring in traffic camera, criminal and security monitoring in the certain local area of concern, etc. In the traffic control field, a case study on analysis and control of traffic conditions by automatic object detection has carried out in this paper. The summaries are given as follows. According to, an on-road vehicle detection system for the self-driving car was developed. This system detects vehicle object and classifies the type of vehicle by Convolutional Neural Network (CNN). The vehicle object tracking algorithm tracks the vehicle object by changing the tracking center point according to the position of the recognized vehicle object on the image. Then, the monitor shows a localized image like a bird's viewpoint with the visualized vehicle objects, and the system calculates the distance between the driving car and the visualized vehicle objects. This process of the system enables to objectively view the position of the vehicle object so that it can help assistance of the self-driving system. As a result, it can localize the vehicle object in vertical 1.5m, horizontal 0.4m tolerance at the camera. In, another deep learning-based detection system in combination with CNN and Support Vector Machine (SVM) was developed to monitor moving vehicles on urban roads or highways by satellite. This system extracts the feature from the satellite image through CNN using the satellite image as an input value and performs the binary classification with SVM to detect the vehicle BBox. Besides, Arinaldi, Pradana, and Gurusinga developed a system to

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estimate the speed of the vehicle, classify vehicle type, and analyze traffic volume. This system utilizes BBox obtained by object detection based on videos or images. The algorithm applied to the system was compared with the Gaussian Mixture Model SVM and faster RCNN. Then it appears that faster R-CNN was able to detect the position and type of vehicle more accurately. In other words, it could be said that the deep learning-based object detection approach is superior to the algorithm based object detection system. As a conclusion, all of the development cases in this paper deal with object information, showing outstanding performance with deep learning. However, they all were hard to assign unique IDs to the detected objects and track them by keeping the same ID over time.

1.1 Motivation

The methods employed by this paper were motivated through observations made on a recently established visual MOT benchmark. Firstly, there is a resurgence of mature data association techniques including Multiple Hypothesis Tracking (MHT) and Joint Probabilistic Data Association (JPDA) which occupy many of the top positions of the MOT benchmark. Secondly, the only tracker that does not use the Aggregate Channel Filter (ACF) detector is also the top ranked tracker, suggesting that detection quality could be holding back the other trackers. Furthermore, the trade-off between accuracy and speed appears quite pronounced, since the speed of most accurate trackers is considered too slow for realtime applications. With the prominence of traditional data association techniques among the top online and batch trackers along with the use of different detections used by the top tracker, this work explores how simple MOT can be and how well it can perform. Keeping in line with Occam's Razor, appearance features beyond the detection component are ignored in tracking and only the bounding box position and size are used for both motion estimation and data association. Furthermore, issues regarding short-term and long-term occlusion are also ignored, as they occur very rarely and their explicit treatment intro duces undesirable complexity into the tracking framework.

We argue that incorporating complexity in the form of object re-identification adds significant overhead into the tracking framework – potentially limiting its use in realtime applications. This design philosophy is in contrast to many proposed visual trackers that incorporate a myriad of components to handle various edge cases and detection errors. This work instead focuses on efficient and reliable handling of the common frame-to-frame associations. Rather than aiming to be robust to detection errors, we instead exploit recent advances in visual object detection to solve the detection problem directly. This is demonstrated by comparing the common ACF pedestrian detector with a recent convolutional neural network (CNN) based detector . Additionally, two classical yet extremely efficient methods, Kalman filter and Hungarian method, are employed to handle the motion prediction and data association components of the tracking problem respectively. This minimalistic formulation of tracking facilitates both efficiency and reliability for online tracking, In this paper, this approach is only applied to tracking pedestrians in various environments, however due to the flexibility of CNN based detectors , it naturally can be generalized to other objects classes. The main contributions of this paper are:

• We leverage the power of CNN based detection in the context of MOT.
• A pragmatic tracking approach based on the Kalman filter and the Hungarian algorithm is presented and evaluated on a recent MOT benchmark.
• Code will be open sourced to help establish a baseline method for research experimentation and uptake in collision avoidance applications.

1.2 Problem Definition

Traditionally MOT has been solved using Multiple Hypothesis Tracking (MHT) or the Joint Probabilistic Data Association (JPDA) filters, which delay making difficult decisions while there is high uncertainty over the object assignments. The combinatorial complexity of these approaches is exponential in the number of tracked objects making them impractical for realtime applications in highly dynamic environments. Recently, Rezatofighi et al., revisited the JPDA formulation in visual MOT with the goal to address the combinatorial complexity issue with an efficient approximation of the JPDA by exploiting recent developments in solving integer programs. Similarly, Kim et al. used an appearance model for each target to prune the MHT graph to achieve state-of-the-art performance. However, these methods still delay the decision making which makes them unsuitable for online tracking. Many online tracking methods aim to build appearance models of either the individual objects themselves or a global model through online learning. In addition to appearance models, motion is often incorporated to assist associating detections to tracklets . When considering only one-to-one correspondences modelled as bipartite graph matching, globally optimal solutions such as the Hungarian algorithm can be used . The method by Geiger et al. uses the Hungarian algorithm in a two stage process. First, tracklets are formed by associating detections across adjacent frames where both geometry and appearance cues are combined to form the affinity matrix. Then, the tracklets are associated to each other to bridge broken trajectories caused by occlusion, again using both geometry and appearance cues. This two step association method restricts this approach to batch computation. Our approach is inspired by the tracking component of, however we simplify the association to a single stage with basic cues as described.

1.3 Objectives

Therefore, in this paper, an attempt is made for generate an object detection & tracking system (ODTS), that can obtain moving information of target objects by combining object tracking algorithm with the deep learning-based object detection process. The full ODTS procedures will be described in details in the following section. Also, the tunnel accident detection system in the framework of ODTS will be taken into consideration. This system is used for detecting accident or unexpected events taking place on moving object and target local region on CCTV.

a lean implementation of a tracking-bydetection framework for the problem of multiple object tracking (MOT) where objects are detected each frame and represented as bounding boxes. In contrast to many batch based tracking approaches , this work is primarily targeted towards online tracking where only detections from the previous and the current frame are presented to the tracker. Additionally, a strong emphasis is placed on efficiency for facilitating realtime tracking and to promote greater uptake in applications such as pedestrian tracking for autonomous vehicles. The MOT problem can be viewed as a data association problem where the aim is to associate detections across frames in a video sequence. To aid the data association process, trackers use various methods for modelling the motion and appearance of objects in the scene.

II.LITERATURE SURVEY

1) Bird’s eye view localization of surrounding vehicles :Longitudinal and lateral distance estimation with partial appearance

AUTHORS: E. S. Lee, W. Choi, D. Kum

On-road vehicle detection is essential for perceiving driving settings, and localizing the detected vehicle helps drivers predict possible risks and avoid collisions. However, there are limited works on vehicle detection with partial appearance, and the method for partially visible vehicle localization has not been explored. In this paper, a novel framework for vehicle detection and localization with partial appearance is proposed using stereo vision and geometry. First, the original images from the stereo camera are processed to form a v-disparity map. After object detection using v-disparity, vehicle candidates are generated with prior knowledge of possible vehicle locations on the image. Deep learning-based verification completes vehicle detection. For each detected vehicle, partially visible vehicle tracking algorithm is newly introduced. To track partially visible vehicles, this algorithm detects the vehicle edge on the ground, defined as the grounded edge, and then selects a reference point for Kalman filter tracking. Finally, a rectangular box is drawn on the bird’s eye view to represent vehicle’s longitudinal and lateral location. The proposed system successfully performs partially visible vehicle detection and tracking. For testing the localization performance, the datasets in a highway and an urban setting are used and provide less than 1.5 m longitudinal error and 0.4 m lateral error in standard deviation.

2) Robust vehicle detection by combining deep features with exemplar classification

AUTHORS: L. Cao, Q. Jiang, M. Cheng, C. Wang

Very recently, vehicle detection in satellite images has become an emerging research topic with various applications ranging from military to commercial systems. However, it retains as an open problem, mainly due to the complex variations in imaging conditions, object intra-class changes, as well as due to its low-resolution. Coming with the

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rapid advances in deep learning for feature representation, in this paper we investigate the possibility to exploit deep neural features towards robust vehicle detection. In addition, along with the rapid growth in the data volume, new classification methodology is also demanded to explicitly handle the intra-class variations. In this paper, we propose a vehicle detection framework, which combines Deep Convolutional Neural Network (DNN) based feature learning with Exemplar-SVMs (E-SVMS) based, robust instance classifier to achieve robust vehicle detection in satellite images. In particular, we adopt DNN to learn discriminative image features, which has a high learning capacity. In our practice, the leverage of DNN has achieve significant performance boost by comparing to a serial of handcraft designed features. In addition, we adopt E-SVMs based robust classifier to further improve the classification robustness, which can be considered as an instance-specific metric learning scheme. By conducting extensive experiments with comparisons to a serial of state-of-the-art and alternative works, we further show that the combination of both schemes can benefit from each other to jointly improve the detection accuracy and effectiveness.

3) Detection and classification of vehicles for traffic video analytics

AUTHORS: A. Arinaldi, J. A. Pradana, A. A. Gurusinga

We present a traffic video analysis system based on computer vision techniques. The system is designed to automatically gather important statistics for policy makers and regulators in an automated fashion. These statistics include vehicle counting, vehicle type classification, estimation of vehicle speed from video and lane usage monitoring. The core of such system is the detection and classification of vehicles in traffic videos. We implement two models for this purpose, first is a MoG + SVM system and the second is based on Faster RCNN, a recently popular deep learning architecture for detection of objects in images. We show in our experiments that Faster RCNN outperforms MoG in detection of vehicles that are static, overlapping or in night time conditions. Faster RCNN also outperforms SVM for the task of classifying vehicle types based on appearances.

III.EXISTING SYSTEM:

In the existing system the data preprocess has dine with structured data. Even though data pre-processing consumes a large chunk of time in an ML pipeline, it is astonishing to see the inadequate amount of work done to automate it. For data preprocessing, it can be noted that while the data pre process approaches are adequate for structured data, work still needs to be done to assimilate on Structured data. We suggest the incorporation of data-mining methods as they can deal with such unformed data. This can allow AutoML pipelines to create models capable of learning from Internet sources. In feature engineering, it should be noted that most methods used until now adhere to supervised learning. However, dataset specificity is high, and therefore, AutoML pipelines should be as generic as possible to accommodate the diverse datasets. Therefore, a gradual paradigm shift towards unsupervised.

DISADVANTAGES OF EXISTING SYSTEM:

Feature Generation is not up to the mark where domain experts excepted results

Most AutoML tools emphasize the performance but in the real world, that’s just one aspect being covered in machine learning projects. So the companies can’t compromise the computing plus storage specification sheet.

CASH(Combined Algorithm Selection and Hyperparameter) problem considers model selection and hyperparameters optimization as a single hierarchical parameter.

Algorithm: SmartML,J48,C50

IV.PROPOSED SYSTEM:

The proposed System aims at providing an overview of the advances seen in the realm of AutoML in recent years. We focus on individual aspects of AutoML and summarize the improvements achieved in recent years. The motivation of proposed system stems from the unavailability of a compact study of the current state of AutoML. While we acknowledge the existence of other surveys, their motive is to either provide an in-depth understanding of a particular segment of AutoML, provide just an experimental comparison of various tools used or are fixated towards deep learning models.

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ADVANTAGES OF PROPOSED SYSTEM:

We segment the AutoML pipeline into parts and review the contributions in each of these segments.

We explore the various state-of-the-art tools currently available for AutoML and evaluate them.

We also incorporate the advancements seen in machine learning which seems to be overshadowed by deep learning in recent years.

Algorithm:H2O-AutoML, LinearRegression, Gradient Boosting Regressor

V.REQUIREMENTS

HARDWARE REQUIREMENTS:

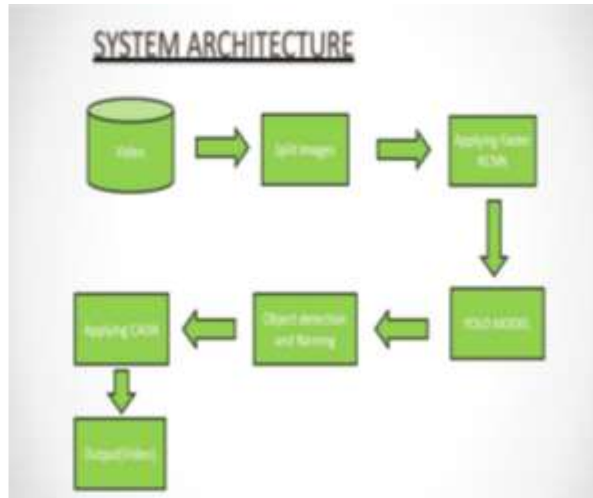
- ❖ **System** : Intel i3
- ❖ **Hard Disk** : 1 TB.
- ❖ **Monitor** : 14' Colour Monitor.
- ❖ **Mouse** : Optical Mouse.
- ❖ **Ram** : 4GB.

SOFTWARE REQUIREMENTS:

- ❖ **Operating system** : Windows 10.
- ❖ **Coding Language** : Python.
- ❖ **Front-End** : Html. CSS
- ❖ **Designing** : Html,css,javascript.
- ❖ **Data Base** : SQLite.

VI.DESIGN

SYSTEM ARCHITECTURE:



6.1 METHODOLOGY

MODULES DESCRIPTION:

User:

User can load the cctv videos. To start the project user has to give –input (Video file path).The open cv class VideoCapture(0) means primary camera of the system, VideoCapture(1) means secondary camera of the system. VideoCapture(Videfile path) means with out camera we can load the pre recorded ideo file to the system. After that user has to load the yolo object detection system which is implemented on RCNN concepts. This yolo module is used for identify the objects from each frame and name that. It can be idenfied humans things fire etc…

Object Detection and Tracking:

Prior detection systems repurpose classifiers or localizers to perform detection. They apply the model to an image at multiple locations and scales. High scoring regions of the bounding box of the image are considered detections. We apply a Regional Convolution neural network to the full image. This network divides the image into regions and predicts bounding boxes and probabilities for each region. These bounding boxes are weighted by the predicted probabilities. Our model has several advantages over classifier-based systems. It looks at the whole image

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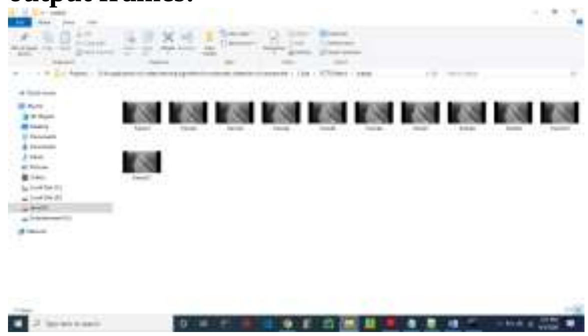
at test time so its predictions are informed by global context in the image.

RCNN(Regional Convolution Neural Network):
R-CNN models first select several proposed regions from an image (for example, anchor boxes are one type of selection method) and then label their categories and bounding boxes (e.g., offsets). Then, they use a CNN to perform forward computation to extract features from each proposed area. Afterwards, we use the features of each proposed region to predict their categories and bounding boxes.Then, based on the detected object information, a dependent object tracking module is initiated to assign the unique ID number to each of the detected objects, IDt and predict the next position of each of the objects, BBOX. The number of tracking BBox u is different from n. But If past tracked BBox is 0, the number of tracking BBox equals to the number of the detected objects.

Average Precision:
AP values for the target objects to be detected, in the training dataset, the number of Car objects is the largest object and very high AP value was obtained for the Car object in comparison with other classes. That is, the object detection performance of deep running of the Car in the video was expected to be highly reliable. On the
other hand, AP for Person object results in relatively low value because Person object exists long, tiny shape in small size. The AP of Fire object was high, but false detection for the object might be highly possible as the number of the objects available for training was very small, Nonetheless, training about deep learning, including No Fire objects, could reduce the false detection of Fire object. However, to detect the Fire in the tunnel control center, it was necessary to collect and involve more images of a Fire event in training.

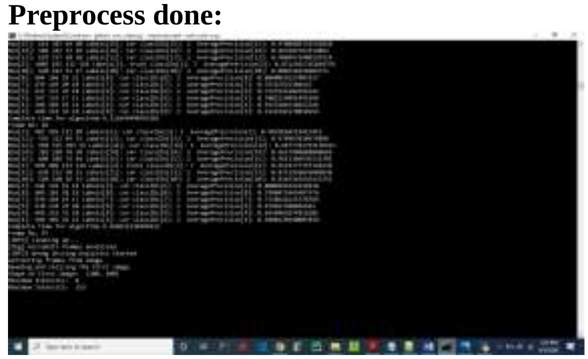
VII. SCREEN SHOTS

output frames:

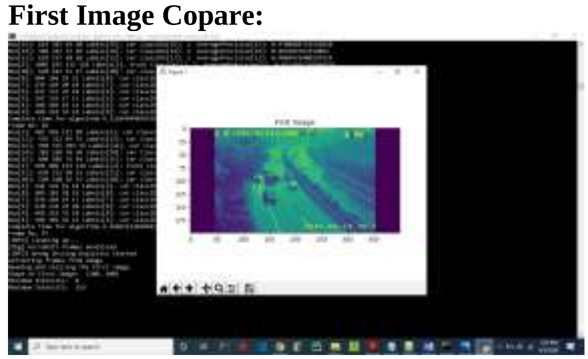


Object Detetction:

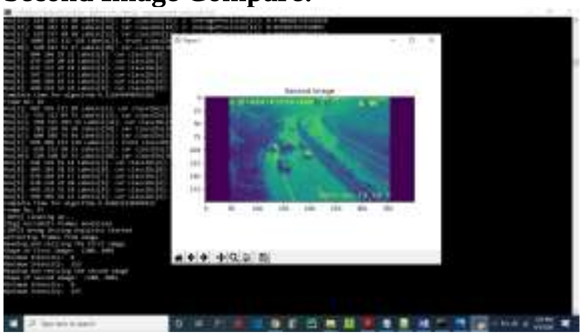
Preprocess done:



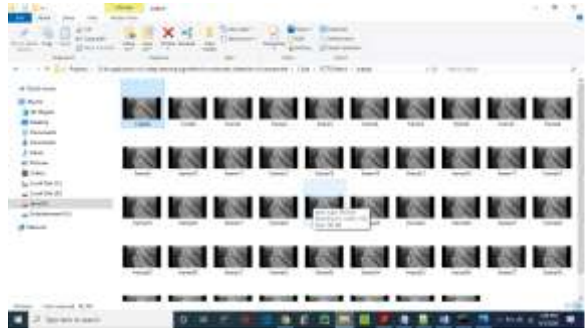
First Image Copare:



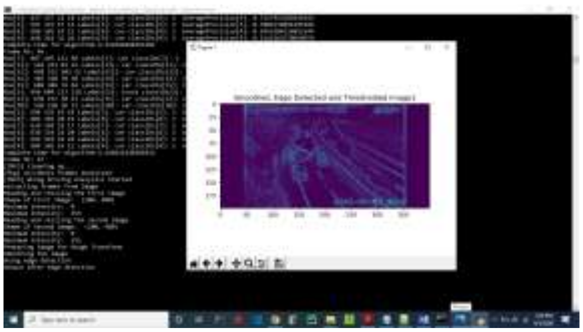
Second Image Compare:



Crash Detected:



Smooth Detetctin:



Identifying driving line:

Space Count:

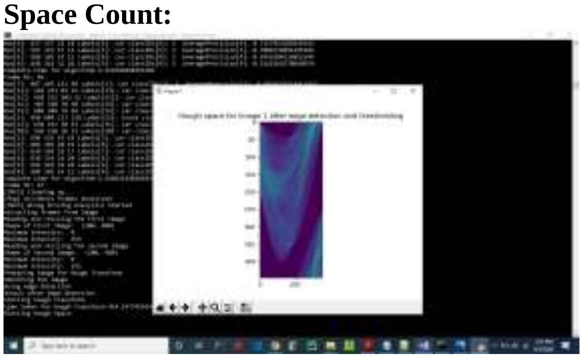
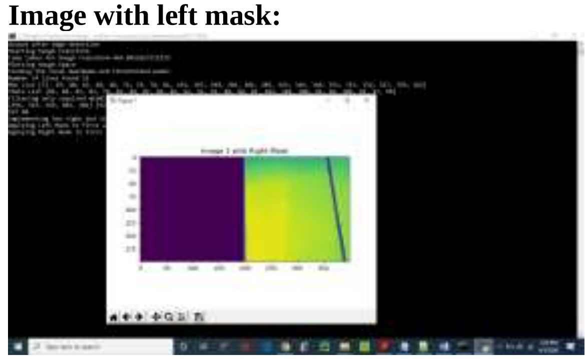
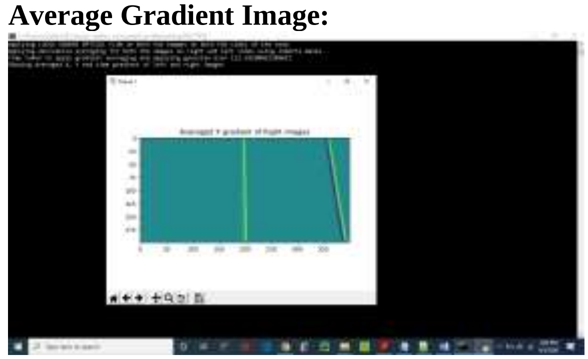


Image with left mask:



Making Video:

Average Gradient Image:



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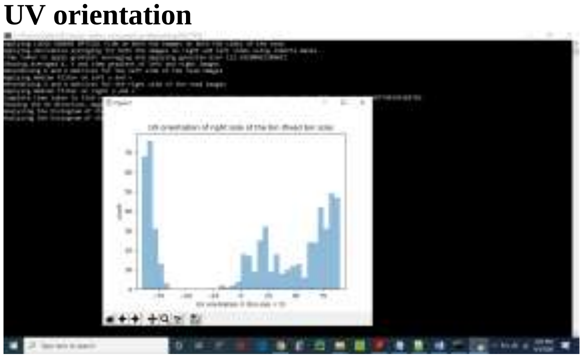
UV orientation:

UV orientation



Detect Vehicle Direction:

VIII.CONCLUSION

This paper proposes a new process of ODTS by combining deep learning-based object detection network and object tracking algorithm, and it shows dynamic information of an object for a specific object class can be obtained and utilized. On the other hand, the object detection performance is important because SORT used in ODTS object tracking uses only information of BBox without using an image. Therefore, continuous object detection performance may be less needed unless the object tracking algorithm is relatively dependent on object recognition performance. And Tunnel CCTV Accident Detection System based on ODTS was developed. The experiments on training and evaluation of deep learning object detection network and detection of an accident of the whole system were conducted. This system adds CADA that discriminates every cycle based on dynamic information of the car objects. As a result of experimenting with the image containing each accident, it was possible to detect the accidents within 10 seconds. On the other hand, training of deep learning secured the object detection performance of a reliable Car object, and Person showed relatively low object detection performance. However, in the case of Fire, there is a high probability of false detection in the untrained videos due to the insufficient number of Fire objects. Nonetheless, it is possible to reduce the occurrence of false detections by simultaneously training objects that are No Fire.

Further Enhancement

The fire object detection performance of the deep learning object detection network should be improved by securing the Fire image later. Although the ODTS can be applied as an example of a Tunnel CCTV Accident Detection System, it is also used to fields that need to monitor the dynamic movement of a specific object such as vehicle speed estimation or illegal parking monitoring will be possible. To increase the reliability of the system, it is necessary to secure various images and to secure Fire and Person objects. Besides, through the application and continuous monitoring of the tunnel management site, the reliability of the system could be improved.

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