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Real Time Object Detection Using Tensor flow

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ABSTRACT *- Detecting and recognizing objects in unstructured as well as structured environments is one of the most challenging tasks in computer vision and artificial intelligence research. This report introduces a new computer vision-based obstacle detection method for mobile technology and its applications. Real time object detection is a challenging task as it needs faster computation power in identifying the object. However the data generated by any real time system are unlabeled data which often need large set of labeled data for effective training purpose. This report proposes a faster detection method for real time object detection based on convolution neural network model called as Single Shot Multi-Box Detection (SSD). Each individual image pixel is classified as belonging either to an obstacle based on its appearance. The method uses a single lens web camera that performs in real-time, and also provides a binary obstacle image at high resolution. The system has been tested successfully in a variety of environments, indoors as well as outdoors.*

I. INTRODUCTION

Obstacle detection is an important task for many mobile technological applications. Most mobile applications rely on range data for obstacle detection. Popular sensors for range based obstacle detection systems include ultrasonic sensors, lasers, radar, stereo vision, optical flow, etc. Because these sensors measure the distances from obstacles to the robot, they are unavoidably suited for the tasks of obstacle detection and obstacle avoidance. But, none of these sensors are perfect. Accurate and reliable detection of these objects require high measurement accuracy and hence precise calibration. Range Sensors have a difficult time in detecting obstacles on the ground surface. While small objects and different types of ground are difficult to detect with range sensors, they can be easily detected with color vision. For this reason, we have developed a new appearance-based obstacle detection system that is based on the technology of artificial intelligence.

II. LITERATURE REVIEW

In various fields, there is a necessity to detect the target object and also track them effectively while handling occlusions and other included complexities. Many researchers attempted for various approaches in object tracking. The nature of the techniques largely depends on the application domain. Some of the research works which made the evolution to proposed work in the field of object tracking are depicted as follows. Moving object detection and tracking Using Convolutional Neural Networks (Shraddha Mane, SupriyaMangale, 2018) Background subtraction is the method which extracts the interested moving object from the video frames. The background subtraction is affected by mostly non-stationary background and illumination changes. In practice, this drawback can be removing by the optical flow algorithm but it is produces false alarm for tracking algorithms under cluttered conditions.

To overcome this limitation, in this approach a novel and generalized Tensor flow based object detection and CNN based object tracking algorithm has been presented. These approaches are robustly detected and track the object in complex scenes and complicated background conditions. CNN is based learner because it is demonstrated to extract the local visual features and they are used in the recognition algorithms. CNNs require the extraction of local characteristics by limiting the receptive fields of the hidden units as local, based on the fact that the images have strong local two-dimensionalstructures. The convolutional neural network combines three architecturalideas to guarantee a certain degree of invariance of change and distortion: local receptive fields, shared weights (or pending replication) and sometimes, spatial and temporal sub sampling.
Object Detection Based on YOLO Network (Chengji Liu, Yufan Tao, Jiawei Liang, Kai Li, Yihang Chen, 2018)In this paper, we simulated different degenerative processes of images for analysis and research. Firstly, we established the models of degraded images. We mainly used mathematical models to generate degraded images which are based on standard data sets. Then, we used these models to train the network to adapt to the complex real-world environment. Finally, we improved the ability of the model to generalize complex images.

We took the traffic signs as the research object and used the YOLO [14] neural network to analyze. The experiment was based on the Darknet-53 network structure.

The YOLO neural network integrates the candidate boxes extraction, feature extraction and objects classification methods into a neural network. The YOLO neural network directly extracts candidate boxes from images and objects are detected through the entire image features.The results show that the model improves the average precision of the object detection. The model which is trained with the degraded training sets has better generalizing ability and higher robustness.

III. EXISTING SYSTEM

3.1 R-CNN

To circumvent the problem of selecting a huge number of regions, Ross Girshick et al. proposed amethod where we use the selective search for extract just 2000 regions from the image and he calledthem region proposals. Therefore, instead of trying to classify the huge number of regions, you canjust work with 2000 regions. These 2000 region proposals are generated by using the selective searchalgorithm which is written below.

3.2 Selective Search:

1. Generate the initial sub-segmentation, we generate many candidate regions
2. Use the greedy algorithm to recursively combine similar regions into larger ones.
3. Use generated regions to produce the final candidate region proposals

3.3 Fast R-CNN

The same author of the previous paper (R-CNN) solved some of the drawbacks of R-CNN to build afaster object detection algorithm and it was called Fast R-CNN. The approach is similar to the R-CNNalgorithm. But, instead of feeding the region proposals to the CNN, we feed the input image to the CNN to generate a convolutional feature map. From the convolutional feature map, we can identify theregion of the proposals and warp them into the squares and by using an RoI pooling layer we reshapethem into the fixed size so that it can be fed into a fully connected layer. From the RoI feature vector,we can use a softmax layer topredict the class of the proposed region and also the offset values for the bounding box.

The reason "Fast R-CNN" is faster than R-CNN is because you don't have to feed 2000 regionproposals to the convolutional neural network every time. Instead, the convolution operation is alwaysdone only once per image and a feature map is generated from it.

3.4 YOLO – You Only Look Once

All the previous object detection algorithms have used regions to localize the object within the image.The network does not look at the complete image. Instead, parts of the image which has highprobabilities of containing the object. YOLO or You Only Look Once is an object detection algorithm much different from the region based algorithms which seen above. In YOLO a single convolutional network predicts the bounding boxes and the class probabilities for these boxes.

YOLO works by taking an image and split it into an SxS grid, within each of the grid we take mbounding boxes. For each of the bounding box, the network gives an output a class probability andoffset values for the bounding box. The bounding boxes have the class probability above a threshold value is selected and used to locate the object within the image.YOLO is orders of magnitude faster (45 frames per second) than any other object detection algorithms.The limitation of YOLO algorithm is that it struggles with the small objects within the image, forexample, it might have difficulties in identifying a flock of birds. This is due to the spatial constraints of the algorithm.

3.5 LIMITATIONS IN EXISTING SYSTEM

YOLO imposes strong spatial constraints on the bounding box predictions since each of the grid cells only predicts two boxes and can have only one class. This spatial constraint then limits the number of nearby objects that our model can predict. The model struggles with the small objects that appear in groups. Since the model learns to predict bounding boxes from data, it however struggles to generalize objects in new or unusual aspect configurations.

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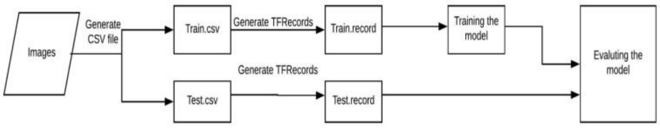
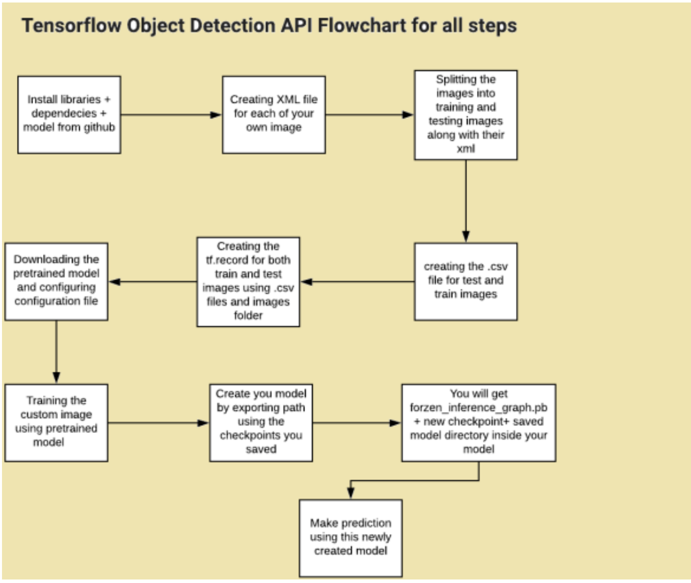
IV. PROPOSED SYSTEM

Proposed system is using method of Single Shot Multibox Detector (SSD). By using SSD, we only need to take one single shot to detect multiple objects within the image, while regional proposal network (RPN) based approaches such as R-CNN series that need two shots, one for generating region proposals, one for detecting the object of each proposal. Thus, SSD is much faster compared with two-shot RPN-based approaches.

4.1 ADVANTAGES OF PROPOSED SYSTEM

- Convolutional neural networks provide an advantage over feed-forward networks because they are capable of considering locality of features.
- Convolutional Neural Network has the ability to handle large unstructured data.
- CNN are more powerful than machine learning algorithms and are also computationally efficient.
- SSD achieves 76.9% mAP at 22 FPS, which outperforms Faster R-CNN (73.2% mAP at 7 FPS) and YOLOv1 (63.4% mAP at 45 FPS).
- SSD attains a better balance between swiftness and precision.





V. SYSTEM IMPLEMENTATION

The system is proposed to have following modules:

- Setting up Anaconda Virtual Environment
- Installation of Packages
- Cloning of Tensorflow Models Repository
- Dataset Model
- Webcam Setup

Setting up Anaconda Virtual Environment

Download and install Anaconda Navigator.

Under the Environments tab, click Create and name the new environment.

Installation of Packages

In the Search Packages box, type the name of the required packages and install the packages.

Select the required version from the packages list.

Cloning of Tensorflow Models Repository

Clone or Download TensorFlow's Model from Github.

From this point on, this directory will be referred to as the models directory.

Dataset Model

Download the model which is trained on the COCO dataset. COCO stands for Common Objects in Context; this dataset contains around 330K labeled images. The model selection is important as you need to make an importanttradeoff between Speed and Accuracy. Depending upon the requirement and the system memory, the correct model must be selected.We are using ssd_mobilenet_v1_coco_11_06_2017.

This is a faster option, which detects video feeds at high FPS rates and simultaneously determines all the bounding box probabilities.The code will download that model from the internet and extract the frozen inference graph of that model.The images are converted into a numPy array for processing.

Webcam Setup
For this module, we are going to be using OpenCV. This code will use OpenCV that will, in turn, use the camera object initialized earlier to convert the video stream into frames.

VI. CONCLUSION

By using this thesis and based on experimental results we are able to detect object more precisely andidentify the objects individually with exact location of an object in the picture in x,y axis.This report also provides experimental results on different methods for object detection and identification andcompares each method for their efficiencies.

TensorFlow provides considerably better and more straightforward support for saving and loading models across a wide range of contexts and programming languages. TensorFlow is useful for loading and storing models. This report presents a new method for obstacle detection with a single webcam. It also presents a new method of vision-based surveillance for general purposes in indoor and outdoor environments.

VII. FUTURE ENHANCEMENTS

- The local or global library used for recognition can be increased, to increase the efficiency of the object recognition system.
- Using unsupervised classifier instead of a supervised classifier forrecognition of the object.

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