FPGA: Deep Learning Applied on Advanced Driving Assistance Systems Under Low Light Environment

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Motivation

A few years ago, a fatal self-driving car accident occurred in US in the middle of the night. The autonomous driving system failed to alert the driver of a passerby early enough, only warning the driver 1.3 second before the deadly impact. As object detection and low-light image enhancement evolves swiftly over the years, we may utilize these technologies. We want to design a system that detects objects under low-light environment. Also, we would attempt to accelerate the framework using the OpenVINO Starter Kit.

Introduction

EnlightenGAN[1]:

EnlightenGAN utilizes un-paired dark/bright image dataset to enhance dark images. The model can be separated into two parts: the generator(G) and the discriminator(D). G generates enhanced images from the low-light images, whereas D strives to discriminate generated bright images from the real ones; G and D are trained in an adversarial manner.

Since EnlightenGAN does not require paired images, we can combine multiple dark image datasets to train a more robust model. For this project, we directly use the model pre-trained in [1] for inference.

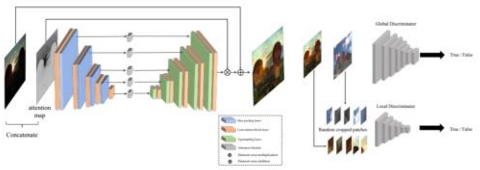


Fig 1. Architecture of EnlightenGAN

YOLO[2]:

YOLO is a well-known framework for object detection. By directly predicting the bounding-box coordinates (relative to the anchor boxes), confidence and class probabilities using the full image, YOLO greatly speeds up the training and inference time, while maintaining high accuracy.

References:

[1] EnlightenGAN: Deep Light Enhancement without Paired Supervision

[2] YOLOv3: An Incremental Improvement

Experiments

Intel OpenVINO Starter Kit (FPGA):

OpenVINO Toolkit kit is a deep learning deployment toolkit. In this project, we mainly manipulate Deep Learning Deployment Toolkit within it. It includes inference engine plugins (CPU, GPU, FPGA, etc) to run models, model optimizer to covert and optimize existing models from other frameworks to intermediate reference for inference engine to infer, and sets of prebuilt DL models.

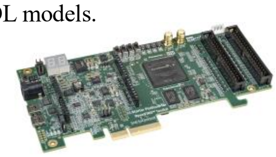


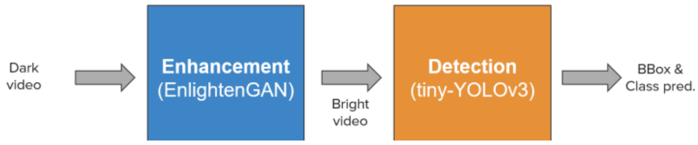
Fig 2. OpenVINO Starter Kit

Experiments

- Openvino Manipulation:

1. Train maching learning model
2. Transfer the PyTorch model into Onnx and verify the result
3. Transfer the Onnx model into Intermediate Representation for OpenVINO Toolkit to inference and verify the result

- Workflow:



Results

We applied brightened images from EnlightenGAN and train tiny-YOLOv3 on the Ex-Dark dataset for 250 epochs.
mAP on validation set: 0.40

Below are our qualitative results on the validation set of Ex-Dark dataset, with the left side being the original images and the right side being the enhanced images with detection results. We can clearly see that after enhancement, the contours of dark regions in the original images become much clearer, thus enabling better object detection.

Conclusion

Under low light environment, it is not easy to detect the objects in the photos; the mAP of YOLOv3 without enhancement is less than 10%. However, after doing proper arrangement of data workflow, we can increase mAP to 40%, compared to 60% under normal light environment. In addition, the total inference speed on a single GPU can be up to 80 FPS, which makes it possible for real-time application. Our ultimate goal is building a solid early warning system to reduce the accident rate. In the future, we will consider changing the labels of the dataset from names of identified objects to risky objects, to increase the recognition rate of risk factors by reducing types of identification.

In addition, we will continue the effort to put the model on OpenVINO Starter Kit for acceleration, to achieve real-time inference on peripheral devices. We hope the final result will be the future of self-driving cars, and that we could contribute to the improvement of road safety.