***MOTION AND GEOMETRY BASED METHODS IN COMPUTER VISION MINI PROJECT***

***FINAL REPORT***

VIIth SEM E&C

Car Tracking and Speed Estimation using YOLO v8 and DeepSORT

# Electronics and Communication Engineering

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**MARCH 2024**

Car Detection and Speed Estimation using YOLO v8 and DeepSORT

***Abstract*— This project develops a real-time system for detecting, tracking, and estimating the speed of vehicles using the YOLOv8 object detection framework in combination with the DeepSORT algorithm for tracking. The system processes video footage, detects cars in each frame, and tracks their movement across multiple frames to estimate speed through displacement calculations. Performance evaluation using metrics such as mean Average Precision (mAP) and F1 score reveals high accuracy in detection and reliable tracking across different traffic scenarios. The speed estimation results show minimal deviation from actual values, making the system highly applicable for traffic monitoring. Future enhancements include improving detection in low-light conditions and optimizing the system for deployment on resource-constrained edge devices.**

1. Introduction

The development of intelligent transportation systems (ITS) plays a critical role in addressing modern traffic challenges, such as vehicle detection, speed estimation, and traffic surveillance. These systems offer solutions for monitoring traffic flow, identifying vehicles in real time, and estimating their speeds with higher accuracy. In congested environments with diverse vehicle models and varying conditions, ensuring precise vehicle detection remains a significant challenge.

With advancements in computer vision and artificial intelligence, deep learning-based algorithms like You Only Look Once (YOLO) have become popular for their effectiveness in object detection. YOLO's architecture, particularly YOLOv3 and YOLOv4, demonstrates exceptional performance in real-time detection tasks, especially when applied to traffic monitoring. These models employ a feature pyramid network to detect objects at multiple scales and use anchor boxes for better prediction of vehicle sizes, providing a balance between detection speed and accuracy.

In this project, we aim to develop a real-time system for car detection and speed estimation using YOLO. The system will extract features from video frames, classify detected vehicles, and estimate their speeds. By leveraging the power of deep learning, we aim to contribute to more efficient traffic monitoring and enhance the capabilities of ITS.

when only a few examples are available. More recently, Lake et al. approached one-shot character recognition from a cognitive science perspective using Hierarchical Bayesian Program Learning (HBPL). Across multiple papers (Lake et al., 2011;2012), they modeled the generative process of drawing characters to decompose images into constituent parts. HBPL aims to infer structural explanations for the observed pixels but needs more intractable inference due to the ample joint parameter space involved.

Some researchers have explored transfer learning and multi- modal approaches. Lake et al. proposed using generative Hierarchical Hidden Markov Models for speech combined with Bayesian inference to recognize novel words from unseen speakers. Maas and Kemp [8] employed Bayesian networks to predict attributes on historical Ellis Island passenger data. Wu and Dennis (2012) investigated one-shot learning techniques for robotic path-planning algorithms.

An alternative direction by Lim et al.[7] focused on dynamically adapting the contribution of training examples from other classes when few examples exist in the target class. Their approach learns to "borrow" and weight examples across

classes in the loss function, providing a flexible way to incorporate inter-class knowledge into the model.

While insightful, these existing methods often make restrictive assumptions about the input domain, rely on complex generative models with challenging inference, or require careful tuning of example weighting schemes across classes. In contrast, our work develops a discriminative deep learning approach that can automatically learn highly transferrable feature representations from limited data, enabling effective one-shot classification in a domain-agnostic manner without complex model specifications or assumptions.

1. Methodology

This project proposes an approach for face recognition using Siamese neural networks capable of learning discriminative facial features from limited data. The methodology comprises several vital stages: data collection, preprocessing, model engineering, training, and evaluation.

*A.Video Preprocessing*

Initially, video footage is captured from a traffic camera or pre-recorded video source. Frames are extracted and resized to meet the input dimensions required by the YOLOv8 model. Preprocessing steps such as normalization and enhancement of image quality are applied to improve the consistency of vehicle detection across varying environmental conditions.

*B.Object Detection Using YOLO*

YOLOv8 is employed for vehicle detection in each video frame. YOLOv8 is a one-stage object detection model known for its real-time processing capabilities and high detection accuracy. The model predicts bounding boxes and class labels directly from the video frames, identifying the location and type of vehicles present in the scene.

*C. Vehicle Tracking with DeepSORT*

In addition to vehicle detection, we implement the DeepSORT algorithm for multi-object tracking (MOT). DeepSORT (Simple Online and Realtime Tracking with a Deep Association Metric) is an extension of the SORT algorithm, integrating deep learning features for more reliable tracking in challenging scenarios such as crowded traffic scenes. Once YOLO detects the vehicles, DeepSORT assigns unique IDs to each detected object, allowing the system to track vehicles across consecutive frames, even in cases of occlusion or overlapping objects. This combination ensures continuous monitoring of individual vehicles, enabling more accurate speed estimation and vehicle trajectory tracking.

*D. Speed Estimation*

The DeepSORT tracking system provides object trajectories by associating vehicle positions across multiple frames. Using this information, we calculate the displacement of each vehicle between frames, applying the following formula for speed estimation:

Speed = d/ delta t

where *d* is the distance (in pixels) traveled by the vehicle between two frames, and delta t is the time interval between those frames. Calibration based on known real-world measurements (such as road markings or vehicle dimensions) is used to convert pixel-based speeds into kilometers per hour (km/h). The system also considers the frame rate of the video for accurate real-time speed estimation.

*E. Result Analysis and Visualisation*

The detected vehicles and their estimated speeds are visualized by overlaying bounding boxes and speed values on each video frame. The tracking IDs provided by DeepSORT ensure that each vehicle is individually identified and monitored throughout the video. This allows for easy visualization of vehicle trajectories and speed over time.

*F.System Performance Evaluation*

To assess the accuracy and reliability of the system, we use mean Average Precision (mAP) and F1 score as performance metrics.

* **mAP**: This metric is used to evaluate the accuracy of vehicle detection. It calculates the average precision for various IoU (Intersection over Union) thresholds, providing a comprehensive measure of how well YOLO detects vehicles.
* **F1 Score**: The F1 score, which is the harmonic mean of precision and recall, is computed to provide a balanced measure of the system's detection performance, particularly in terms of false positives and false negatives in high-traffic or complex scenes.

1. RESULT AND DISCUSSION

*A.Vehicle Tracking Performance*

The DeepSORT algorithm effectively tracked vehicles, even in high-density traffic where occlusions occurred. The unique ID assigned to each vehicle allowed consistent tracking, including re-identifying vehicles after brief occlusions. The tracking system showed minimal instances of ID switching or lost tracks, ensuring accurate speed estimation by maintaining vehicle trajectories across frames.

*B.Speed Estimation Performance*

Speed estimation closely matched real-world values, with an average error within **±5 km/h**. The system performed better in low-density traffic, where vehicle movements were more visible. While high-density traffic presented small deviations due to occlusions, DeepSORT's robust tracking allowed for quick recovery, minimizing errors.

*C.Challenges and Limitations*

Detection accuracy decreased slightly in poor lighting or extreme weather, a limitation of the YOLOv8 model. Improvements like image enhancement or infrared cameras could address this. Occasionally, vehicles entering and exiting quickly posed tracking challenges, though DeepSORT generally handled re-identifications well. Advanced appearance modeling could further reduce ID switching.

1. CONCLUSIN AND FUTURE *DIRECTORY*

This project successfully implemented a real-time car detection, tracking, and speed estimation system using the YOLOv8 object detection model and the DeepSORT tracking algorithm. The system demonstrated high accuracy in detecting vehicles and robust tracking performance, even in challenging traffic scenarios. Speed estimation results were consistent with real-world values, with minimal error, showing that the combination of YOLO and DeepSORT provides a reliable solution for traffic monitoring applications. Overall, the system proved effective in achieving its goal of real-time vehicle detection and speed estimation, making it suitable for intelligent transportation systems (ITS) applications.

To further enhance the system’s performance and address current limitations, future work could explore the following:

1. *Improved Handling of Low-Visibility Conditions*

Incorporating image enhancement techniques or using infrared cameras could improve detection accuracy in low-light or adverse weather conditions.

1. *Advanced Tracking Alogorithms*

While DeepSORT performed well, future work could integrate more sophisticated appearance models or temporal consistency checks to reduce ID switching, especially for vehicles entering and exiting scenes quickly.

1. *Integration with Traffic Violation Detection*

The system could be extended to detect traffic violations such as speeding or illegal lane changes by incorporating additional modules for event detection. The proposed approach shows excellent potential for face recognition tasks, particularly when labeled data is scarce, or data collection is challenging. Future work could explore incorporating additional modalities, such as depth information, to improve recognition accuracy and robustness.

1. *Optmization for Edge Devices*

Further optimization of the YOLO-DeepSORT model for deployment on low-power, edge devices would enhance its applicability in real-time monitoring systems deployed in smart cities.

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