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Vehicle Detection and Speed Tracking

Lakshmi M D, Sidharth P, Liya Prakash
Dept. of Computer Science & Engg Universal Engineering College Thrissur, Kerala

Abstract: Accurate vehicle speed estimation is essential for traffic monitoring, road safety, and intelligent transportation systems. Conventional methods such as radar, LiDAR, and embedded sensors provide reliable measurements but involve high installation and maintenance costs, limiting their scalability. This paper presents a vision-based vehicle detection and speed tracking system that utilizes existing surveillance cameras without requiring additional hardware. The proposed system integrates YOLOv3 for real-time vehicle detection, DeepSORT for multi-object tracking, and the Pyramidal Lucas–Kanade optical flow algorithm for fine-grained motion analysis. Four virtual intrusion lines are defined within the camera's field of view to extract temporal and spatial features, enabling speed estimation using both distance-over-time and time-over-distance approaches. Additionally, a Multilayer Perceptron (MLP) model is employed to further improve prediction accuracy. Experimental results demonstrate that the system achieves a Mean Absolute Error (MAE) of approximately 3.07 km/h and a Root Mean Square Error (RMSE) of 3.98 km/h under real traffic conditions. The proposed method offers a cost-effective, scalable, and non-intrusive solution for real-time vehicle speed estimation, contributing to the development of smart traffic monitoring systems.
Index Terms— Vehicle Detection, Speed Estimation, YOLOv3, DeepSORT, Optical Flow, Intelligent Transportation Systems

I. INTRODUCTION

Accurate measurement of vehicle speed plays a vital role in modern traffic management, law enforcement, and intelligent transportation systems. Reliable speed information is essential for detecting traffic violations, monitoring congestion, and analyzing vehicle flow patterns. Conventional systems such as radar guns, inductive loop sensors, and laser-based devices provide high accuracy but involve significant installation and maintenance costs. In addition, their deployment often requires infrastructural modifications that may disrupt normal traffic flow, making them less suitable for large-scale implementation.

With the rapid growth of surveillance camera networks in urban areas, there exists an opportunity to utilize these systems for vehicle speed estimation. Most traffic cameras are already positioned at key locations such as highways and intersections, providing continuous visual data. However, these systems primarily function as passive monitoring tools without analytical capabilities. By integrating computer vision and deep learning techniques, these existing cameras can be transformed into intelligent systems capable of detecting, tracking, and estimating vehicle speed in real time.

The purpose of this project is to develop a vision-based vehicle detection and speed tracking system that operates using video data from surveillance cameras. The proposed approach eliminates the need for additional hardware sensors by relying entirely on software-based techniques such as object detection, multi-object tracking, and optical flow analysis. This enhances the utility of existing infrastructure while reducing implementation costs and improving efficiency in traffic monitoring systems.

Despite its advantages, video-based speed estimation presents several challenges, including camera calibration, perspective distortion, varying environmental conditions, and occlusion in dense traffic scenarios. The proposed system addresses these issues by integrating YOLOv3 for vehicle detection, DeepSORT for tracking, and optical flow techniques for motion analysis, enabling accurate and scalable speed estimation. This approach contributes to the development of cost-effective and intelligent traffic monitoring solutions aligned with modern smart city initiatives.

II. RELATED WORKS

Our project draws on and combines several major advancements in end-to-end speech translation, affective computing, and modern neural speech synthesis.

A. Intrusive Sensor-Based Systems

Intrusive vehicle speed measurement systems such as inductive loop detectors, piezoelectric sensors, and magnetic detectors are embedded directly into the road surface. These systems provide highly accurate speed measurements by detecting vehicle presence at fixed points. However, their installation requires road excavation and causes traffic disruption. Additionally, maintenance and repair are costly, limiting their scalability for large-scale traffic monitoring applications.

B. Non-Intrusive Radar and Laser Systems

Non-intrusive systems, including radar-based speed guns, microwave sensors, and laser-based devices, offer easier deployment without modifying road infrastructure. These systems measure vehicle speed using electromagnetic waves or time-of-flight principles. Although they provide real-time speed estimation, they typically monitor only a single vehicle or lane at a time. Their performance may also be affected by environmental conditions such as rain or fog, and large-scale deployment increases overall system cost.

C. Traditional Vision-Based Methods

Early vision-based approaches used techniques such as background subtraction and frame differencing to detect moving vehicles. These methods estimate speed by measuring pixel displacement across frames. While computationally simple and cost-effective, they are highly sensitive to environmental changes such as lighting variations, shadows, and occlusions. As a result, their accuracy and reliability are limited in real-world traffic scenarios.

D. Deep Learning-Based Vision Systems

Recent advancements in deep learning have enabled more robust vehicle detection and tracking. Models such as YOLO, Faster R-CNN, and RetinaNet, combined with tracking algorithms like SORT and DeepSORT, provide improved accuracy in multi-object tracking. Some approaches also incorporate optical flow and feature tracking techniques for better motion estimation. However, many of these systems require high computational resources, controlled camera angles, or complex calibration. The proposed system addresses these challenges by integrating YOLOv3, DeepSORT, and optical flow techniques to achieve accurate and scalable speed estimation using existing surveillance cameras.

III. SYSTEM ARCHITECTURE

The proposed vehicle detection and speed tracking system is designed as a modular pipeline that processes traffic video data to estimate vehicle speed in real time. The system architecture consists of four major components: video input, vehicle detection, vehicle tracking, and speed estimation. These modules operate sequentially to ensure accurate and efficient processing of traffic scenes.

A. Video Input and Preprocessing

The first stage of the system involves detecting vehicles from input video frames and tracking them across consecutive frames. YOLOv3 is used for real-time vehicle detection due to its high accuracy and efficiency. Each detected vehicle is represented by a bounding box:

B=(x,y,w,h)B=(x,y,w,h)

where xx and yy denote the position, and ww and hh represent the width and height of the detected object.

To maintain continuity, the DeepSORT algorithm is employed for multi-object tracking. It assigns a unique ID to each vehicle and tracks its movement across frames using Kalman filtering and data association techniques. The displacement of a vehicle between frames is computed using the Euclidean distance:

Δd=(xi+1−xi)2+(yi+1−yi)2Δd=(xi+1−xi)2+(yi+1−yi)2

Additionally, optical flow techniques are applied to track feature points, particularly near the wheel regions, to improve motion accuracy and reduce tracking noise.

B. Speed Estimation and Motion Analysis

The second stage involves estimating vehicle speed using motion analysis techniques. Two complementary models are used to improve accuracy:

1) Distance-over-Time Model

v=ΔdΔtv=ΔtΔd

where ΔdΔd is the displacement and Δt=1fpsΔt=fps1 is the time between frames. The computed speed is converted from pixel units to real-world units using calibration parameters.

2) Time-over-Distance Model

Speed is also calculated based on the time taken to cross a known distance LL between virtual intrusion lines:

v=Ln□fpsv=n□fpsL

where nn represents the number of frames required to traverse the distance.

To enhance reliability, temporal motion vectors such as crossing distance and frame count are used for averaging and error reduction. Furthermore, a Multilayer Perceptron (MLP) model is applied to refine speed predictions, improving overall accuracy under real-world conditions.

IV. IMPLEMENTATION DETAILS

A. Detection and Tracking Implementation

The system is implemented using Python and OpenCV, with YOLOv3 employed for real-time vehicle detection. Each input video frame is resized and passed through the YOLOv3 model, which generates bounding boxes around detected vehicles along with confidence scores. These detections are then filtered to retain only relevant vehicle classes.

For tracking, the DeepSORT algorithm is used to maintain consistent identities of vehicles across frames. It combines motion prediction using a Kalman filter with appearance-based feature matching to ensure reliable tracking, even under partial occlusion or temporary detection loss. Each vehicle is assigned a unique ID, and its centroid position is recorded across consecutive frames.

To enhance motion accuracy, the Pyramidal Lucas–Kanade optical flow algorithm is applied to track feature points, particularly around the wheel regions of vehicles. This allows sub-pixel motion estimation and reduces errors caused by bounding box fluctuations. The combination of detection, tracking, and optical flow ensures stable and continuous motion representation for each vehicle.

B. Speed Estimation Implementation

Speed estimation is performed using two complementary models derived from temporal motion analysis. The first approach calculates speed based on pixel displacement between frames, while the second uses predefined spatial references within the video frame.

v=ΔdΔtv=ΔtΔd

In the distance-over-time model, the displacement of a vehicle between consecutive frames is measured and divided by the time interval determined by the frame rate. The computed value is then converted into real-world units using pixel-to-meter calibration factors.

In the time-over-distance model, four virtual intrusion lines are defined within the Region of Interest (ROI). The number of frames required for a vehicle to cross the known distance between these lines is recorded, and speed is calculated accordingly:

v=Ln□fpsv=n□fpsL

where LL is the known distance and nn is the frame count.

To improve estimation accuracy, temporal motion vectors such as crossing distance and frame count are used for averaging and noise reduction. Additionally, a Multilayer Perceptron (MLP) model is trained using these features to refine speed predictions. This hybrid implementation ensures accurate, robust, and reliable speed estimation under varying traffic conditions.

V. EXPERIMENTAL SETUP & EVALUATION

The performance of the proposed vehicle detection and speed tracking system is evaluated using real-world traffic video datasets. The experimental setup is designed to assess the accuracy, reliability, and robustness of the system under practical conditions. The evaluation focuses on detection performance, tracking stability, and speed estimation accuracy.

A. Experimental Setup

The system is tested using traffic videos captured from fixed surveillance cameras with a resolution of 1920 × 1080 and a frame rate of 30 frames per second. A Region of Interest (ROI) is defined within the frame to monitor vehicle movement effectively. Four virtual intrusion lines are placed within the ROI to facilitate temporal and spatial measurements required for speed estimation.

The dataset consists of a controlled set of vehicles with known ground truth speeds measured using a laser speed gun, along with a larger dataset captured under real traffic conditions. In total, the system is evaluated on hundreds of vehicles across varying speeds, lighting conditions, and traffic densities. Only fully visible vehicles are considered to ensure accurate evaluation.

The implementation is carried out using Python with OpenCV and deep learning frameworks. YOLOv3 is used for detection, DeepSORT for tracking, and optical flow techniques for motion analysis. The system processes video frames sequentially and records vehicle positions, displacement, and frame count for speed computation.

B. Evaluation Metrics

The performance of the system is evaluated using standard error metrics to compare estimated speeds with ground truth values. The following metrics are used:

1) Mean Absolute Error (MAE)

$$MAE = \frac{1}{M} \sum_{i=1}^{M} |v_i^g - v_i^e|$$

2) Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{M} \sum_{i=1}^{M} (v_i^g - v_i^e)^2}$$

Where M is the number of vehicles, v_i^g is the ground truth speed, and v_i^e is the estimated speed. These metrics quantify the accuracy and consistency of the proposed system.

C. Results and Performance Analysis

The experimental results demonstrate that the proposed system achieves high accuracy in vehicle speed estimation. The system records a Mean Absolute Error (MAE) of approximately 3.07 km/h and a Root Mean Square Error (RMSE) of approximately 3.98 km/h, indicating reliable performance under real-world conditions.

The integration of optical flow with DeepSORT tracking improves motion continuity and reduces errors caused by bounding box fluctuations. The use of dual speed estimation models (distance-over-time and time-over-distance) enhances robustness by validating results across multiple measurements. Furthermore, the application of a Multilayer Perceptron (MLP) model improves prediction accuracy by learning nonlinear relationships between motion features.

D. Discussion

The system performs effectively under moderate traffic density and varying lighting conditions. It demonstrates strong capability in handling multiple vehicles simultaneously and maintaining tracking consistency. However, certain limitations are observed in cases of heavy occlusion, extreme lighting variations, and significant perspective distortion.

Despite these challenges, the proposed system provides a cost-effective and scalable alternative to traditional sensor-based speed measurement systems. The results confirm that vision-based approaches can achieve comparable accuracy while utilizing existing surveillance infrastructure.

VI. CONCLUSION AND FUTURE WORK

The proposed vehicle detection and speed tracking system demonstrates an effective vision-based approach for estimating vehicle speed using traffic video data. By integrating YOLOv3 for vehicle detection, DeepSORT for multi-object tracking, and optical flow techniques for motion analysis, the system is capable of accurately tracking multiple vehicles and estimating their speed in real time. The use of dual speed estimation models—distance-over-time and time-over-distance—enhances reliability by validating measurements through complementary methods. Experimental results show that the system achieves a Mean Absolute Error (MAE) of approximately 3.07 km/h and a Root Mean Square Error (RMSE) of 3.98 km/h, confirming its accuracy and robustness under real-world traffic conditions.

The system provides a cost-effective and scalable alternative to traditional sensor-based speed measurement methods, as it utilizes existing surveillance infrastructure without requiring additional hardware. It also offers flexibility for deployment in various traffic environments, including urban roads and highways. However, certain limitations remain, such as sensitivity to camera positioning, lighting variations, and occlusion in dense traffic scenarios.

Future work can focus on enhancing the system to support multi-lane vehicle tracking and improving robustness under challenging environmental conditions. Automated camera calibration techniques can be incorporated to reduce manual intervention and improve accuracy. Additionally, integrating advanced deep learning models and real-time processing optimizations can further enhance performance. The system can also be extended with Automatic Number Plate Recognition (ANPR) for traffic enforcement applications, contributing to the development of intelligent and data-driven transportation systems.

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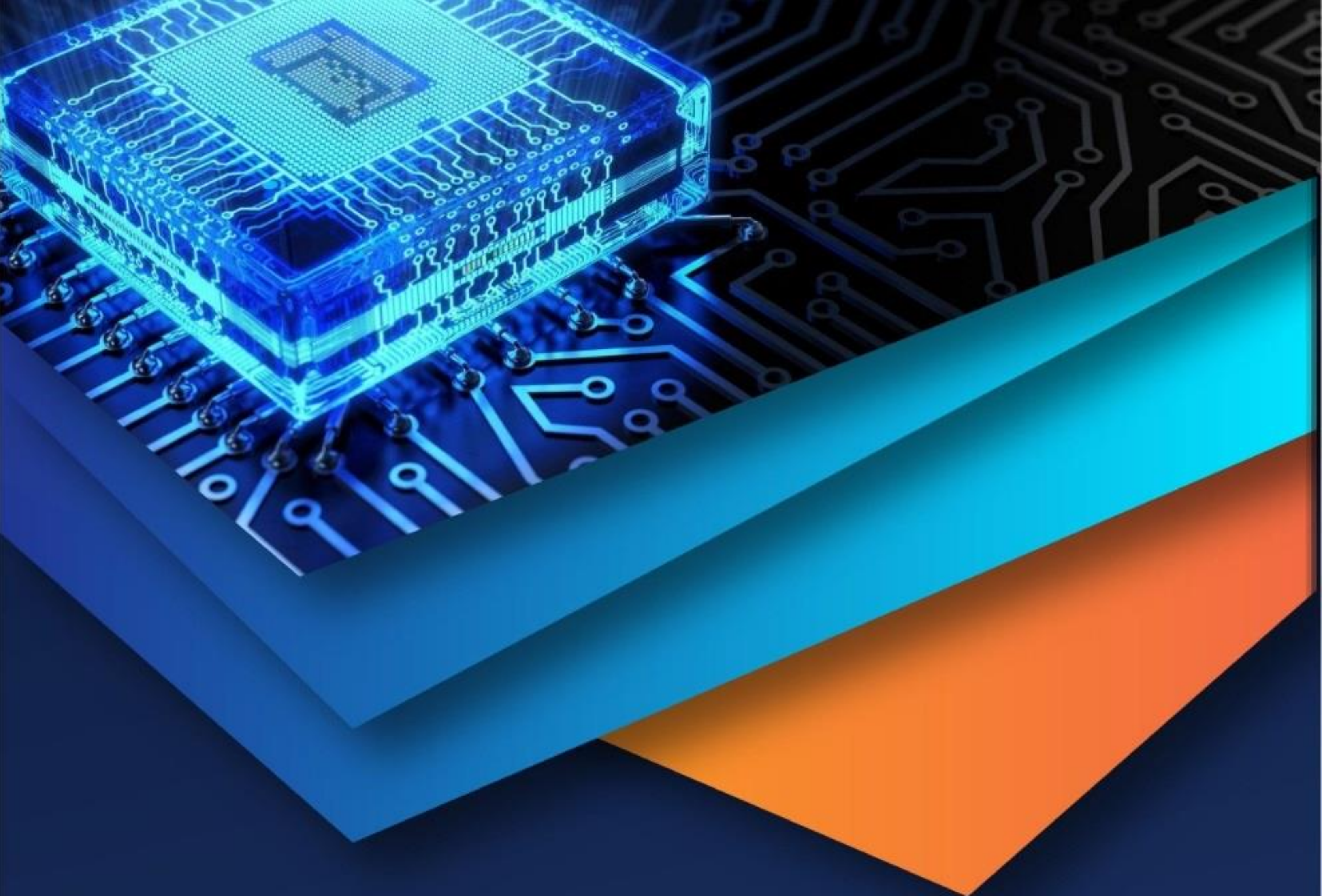

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