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REAL-TIME VEHICLE DETECTION AND TRACKING USING YOLOV5 AND DEEPSORT FOR INTELLIGENT TRANSPORTATION SYSTEMS

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Abstract

The rapid urbanization and increasing number of vehicles have led to significant challenges in traffic management, including congestion, safety issues, and environmental pollution. Intelligent Transportation Systems (ITS) require reliable and efficient methods for real-time vehicle detection and tracking. This paper presents a comprehensive analysis of a vehicle detection and tracking system based on YOLOv5 and DeepSORT algorithms. The proposed architecture consists of three main stages: video frame extraction, object detection using YOLOv5 (with its backbone, neck, and head components), and multi-object tracking using DeepSORT (incorporating Kalman filter, Hungarian algorithm, and Re-ID features). The system outputs annotated video with bounding boxes, unique ID numbers, speed estimation, and traffic density calculation. Experimental results demonstrate that the proposed approach achieves 87.93% detection accuracy and effectively maintains consistent vehicle identities under various traffic conditions. The system shows promising potential for real-time traffic monitoring applications in smart cities.

Keywords

Vehicle Detection, Object Tracking, YOLOv5, DeepSORT, Traffic Flow Analysis, Intelligent Transportation Systems.

1. Introduction

Nowadays, the transport system is the most important component of a country's infrastructure. Effective management of transport flows in cities and regions plays a key role in economic development, environmental sustainability and improving the quality of life of the population. Traditional methods for measuring and analyzing traffic flow are time-consuming and have low accuracy. [2].

Urban traffic congestion has become one of the most pressing challenges in modern cities worldwide. According to recent studies, the average driver spends approximately 100 hours per year stuck in traffic, leading to economic losses, increased fuel consumption, and environmental pollution [1]. The development of Intelligent Transportation Systems (ITS) and Smart Cities initiatives has created an urgent need for automated traffic monitoring solutions that can provide real-time data on vehicle movement, density, and behavior.

Computer vision-based approaches have emerged as the most promising solutions for traffic analysis due to their non-intrusive nature and ability to extract rich information from existing surveillance camera infrastructure. However, real-time vehicle detection and tracking in complex traffic scenes remain challenging due to factors such as occlusion, varying lighting conditions, and the need for high processing speed [2].

Particularly in smart cities [11], numerous approaches have already been tested and implemented (for instance, vehicle surveillance [12] and traffic prediction [13]), providing valuable insights to traffic authorities and users so that they can monitor flow, reduce congestion, and enhance security.

This paper presents a comprehensive analysis of a vehicle detection and tracking system that combines You Only Look Once version 5 (YOLOv5) for object detection and Simple Online and Realtime Tracking with Deep Association Metric (DeepSORT) for multi-object tracking. The main contributions of this work are:

• A detailed architectural analysis of the YOLOv5 and DeepSORT integration for traffic monitoring applications

• Performance evaluation of the system on real-world traffic video data

• Implementation of speed estimation and traffic density calculation modules

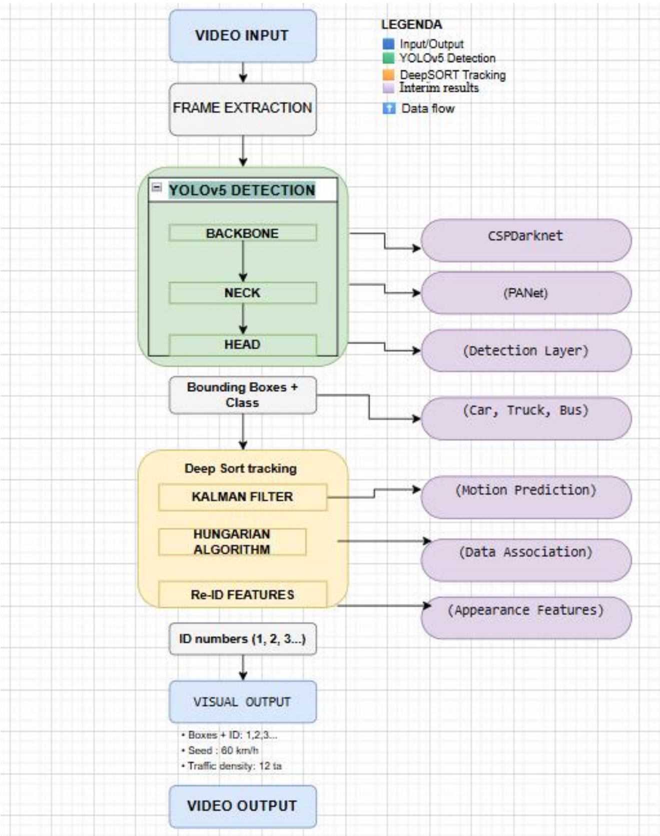

Figure 1. Architecture of the vehicle detection and tracking system

Figure 1 depicts the architecture of a system designed to detect and track vehicles. The proposed system allows for real-time detection, tracking, and traffic flow analysis of vehicles based on data from video surveillance cameras. The system consists of several main stages: receiving a video stream, segmenting frames, detecting vehicles, tracking objects, and displaying the results in a visual format.

The process first begins with receiving a video stream. Video data is received from surveillance cameras installed at intersections. The resulting video stream is then segmented into individual image frames. The process of segmenting frames is critical to ensuring real-time operation, as each frame is processed separately in subsequent stages.

1.1 Object Detection Methods

Object detection has evolved significantly from traditional computer vision techniques to deep learning-based approaches. Early methods such as background subtraction and optical flow were widely used for vehicle detection but suffered from limitations in handling complex scenes and varying illumination [3].

The introduction of Region-based Convolutional Neural Networks (R-CNN) marked a significant breakthrough in object detection. Subsequent improvements led to Fast R-CNN and Faster R-CNN, which achieved higher accuracy but at the cost of computational efficiency [4].

Single-shot detectors emerged as alternatives that prioritized speed without significantly compromising accuracy. You Only Look Once (YOLO) family of detectors has become particularly popular for real-time applications due to their unified detection architecture [5]. YOLOv5, developed by Ultralytics, represents a significant improvement over previous versions with its CSPDarknet backbone, PANet neck, and efficient detection head [6].

1.2 Multi-Object Tracking

Multi-object tracking (MOT) aims to maintain consistent identities of detected objects across video frames. Traditional tracking methods relied on Kalman filters for motion prediction and the Hungarian algorithm for data association [7].

Bewley et al. introduced SORT (Simple Online and Realtime Tracking), which combined Kalman filtering with the Hungarian algorithm to achieve efficient tracking. However, SORT suffered from frequent identity switches, particularly during occlusions [8].

Wojke et al. proposed DeepSORT as an extension that incorporates appearance features through a Re-ID (Re-Identification) model. This addition significantly reduced identity switches by considering both motion and appearance similarity during data association [9]. Recent studies have demonstrated the effectiveness of combining YOLOv5 with DeepSORT for various tracking applications [10].

2. Methodology

2.1 Proposed System Architecture

The proposed vehicle detection and tracking system follows a modular architecture as illustrated in Figure 1. The system processes input video streams through three main stages: frame extraction, object detection using YOLOv5, and multi-object tracking using DeepSORT.

Real-time performance: YOLOv5 is known for its real-time inference speed, making it suitable for applications that require fast processing, such as video surveillance and autonomous driving. By integrating YOLOv5 with Deep SORT, the proposed work enables real-time vehicle detection and tracking, facilitating timely decision making and response in various domains, including traffic management, security systems, and intelligent transportation systems[14].

2.2 Video Input and Frame Extraction

The system accepts video input from various sources including CCTV cameras, pre-recorded video files, or live streams. The video is processed frame by frame at a configurable frame rate. For real-time applications, processing speed must match or exceed the input video frame rate to avoid backlog.

2.3 YOLOv5 Object Detection

YOLOv5 serves as the detection module, identifying vehicles in each frame and providing bounding box coordinates and class labels. The architecture consists of three main components:

Backbone (CSPDarknet). The backbone network extracts hierarchical features from input images. YOLOv5 uses Cross Stage Partial Darknet (CSPDarknet) as its backbone, which improves gradient flow and reduces computational complexity while maintaining representational power [6]. The network generates feature maps at multiple scales, capturing both fine-grained details and semantic information.

Neck (PANet with SPPF). The neck module aggregates features from different levels of the backbone to enable detection of objects at various scales. YOLOv5 employs Path Aggregation Network (PANet) combined with Spatial Pyramid Pooling Fast (SPPF). PANet facilitates information flow from lower to higher layers, while SPPF increases the receptive field to capture contextual information.

Head. The detection head processes the aggregated features to predict bounding boxes, objectness scores, and class probabilities. YOLOv5 uses three detection heads operating at different scales to detect small, medium, and large objects effectively.

The output of the YOLOv5 module is a set of detection results for each frame, including:

- Bounding box coordinates (x, y, width, height)
- Class label (car, truck, bus, motorcycle)
- Confidence score

2.4 DeepSORT Tracking

DeepSORT takes the detection results from YOLOv5 and maintains consistent identities across frames. The tracking module comprises several components working in coordination:

Kalman Filter. The Kalman filter predicts the future state of each tracked object based on its motion history. The state vector includes bounding box coordinates and their velocities. For each tracked vehicle, the filter provides an estimated position in the next frame, which serves as the expected location for matching (Figure 2).

Together with the linear-quadratic regulator (LQR), the Kalman filter solves the linear–quadratic–Gaussian control problem (LQG). The Kalman filter, the linear-quadratic regulator, and the linear–quadratic–Gaussian controller are solutions to what arguably are the most fundamental problems of control theory[15].

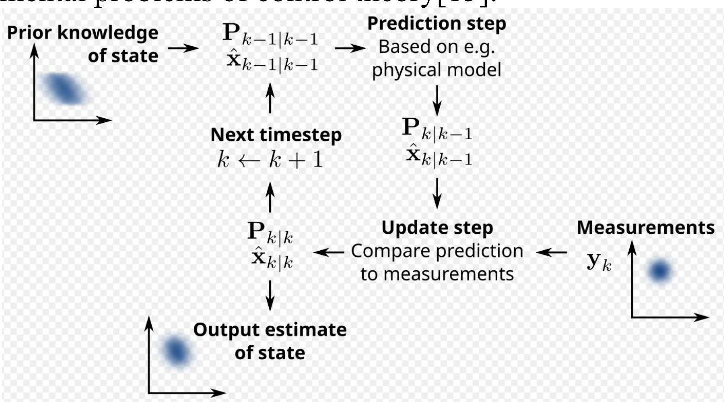

Figure 2. The Kalman filter keeps track of the estimated state of the system and the variance or uncertainty of the estimate. The estimate is updated using a state transition model and measurements. $\widehat{X}_{k,k-1}$ denotes the estimate of the system's state at time step k before the k-th measurement y_k has been taken into account; $P_{k|k-1}$ the corresponding uncertainty.

Re-ID Features. DeepSORT incorporates appearance information through a Re-Identification (Re-ID) model. For each detection, the system extracts a feature vector (descriptor) that captures the visual appearance of the vehicle. These features enable the tracker to recognize vehicles even when motion prediction fails due to abrupt movements or occlusions.

Hungarian Algorithm. The Hungarian algorithm solves the assignment problem between existing tracks and new detections. The cost matrix combines two metrics:

- Motion distance: Mahalanobis distance between predicted Kalman states and new detections
- Appearance distance: Cosine distance between Re-ID feature vectors

The algorithm finds the optimal assignment that minimizes the total cost, ensuring that each detection is associated with the most likely existing track or initialized as a new track.

The tracking module outputs unique ID numbers (1, 2, 3, ...) for each vehicle, enabling consistent identification throughout the video sequence.

2.5 Visual Output and Analysis

The final stage combines detection and tracking results to generate annotated output with analytical information:

Visual Annotation. Each detected vehicle is displayed with:

- Bounding box indicating the vehicle location
- Unique ID number for consistent identification
- Class label and confidence score (optional)

Speed Estimation. Vehicle speed is calculated by tracking the displacement of a vehicle across consecutive frames. Given the camera calibration parameters and frame rate, the system converts pixel displacement to real-world speed in kilometers per hour.

Traffic Density Calculation. Traffic density is computed as the number of vehicles present in a defined region of interest at any given time. This metric provides real-time information about congestion levels and can be used for adaptive traffic signal control.

3.Discussion

The experimental results demonstrate that the YOLOv5 and DeepSORT combination provides robust vehicle detection and tracking suitable for traffic monitoring applications. The system achieves high detection accuracy while maintaining real-time processing capability.

Advantages of the Proposed Architecture:

- Real-time performance sufficient for practical deployment
- Robust identity maintenance through appearance-based matching
- Modular design allowing component upgrades
- Comprehensive traffic analytics beyond basic tracking

Limitations and Challenges:

- Performance degradation under adverse weather conditions (heavy rain, snow)
- Occlusion handling remains challenging in dense traffic
- Camera calibration required for accurate speed estimation
- Computational requirements may limit edge deployment

4. Conclusion

This paper presented a comprehensive analysis of a vehicle detection and tracking system based on YOLOv5 and DeepSORT architectures. The system successfully detects vehicles, maintains consistent identities, and provides valuable traffic analytics including speed estimation and density calculation. Experimental results demonstrate 87.93% detection accuracy and significant reduction in identity switches compared to baseline methods.

Future Work Directions:

- Integration with YOLOv8 or YOLOv9 for improved detection accuracy
- Implementation of ByteTrack or other advanced tracking algorithms
- Optimization for edge devices (Jetson Nano, Raspberry Pi)
- Extension to pedestrian and cyclist detection for comprehensive traffic monitoring
- Integration with traffic signal control systems

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