VEHICLE SPEED ESTIMATION FROM TRAFFIC

CAPSTONE PROJECT REPORT

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Abstract

This paper presents a novel approach for estimating vehicle speed from traffic video footage using computer vision techniques. The proposed method integrates an optimal flow algorithm to enhance the accuracy and robustness of the speed estimation process. By leveraging advanced image processing and machine learning methodologies, the system detects and tracks vehicles across successive frames of traffic videos. The core contribution of this work is the application of an optimal flow algorithm, which minimizes errors in motion estimation by considering both spatial and temporal consistency.

The workflow begins with preprocessing steps, including background subtraction and vehicle detection using convolutional neural networks (CNNs). Detected vehicles are then tracked across frames using a combination of optical flow and Kalman filtering to maintain accurate trajectories. The optimal flow algorithm is employed to refine the estimated motion vectors, which are crucial for precise speed calculation.

Experimental results demonstrate the effectiveness of the proposed method on various traffic datasets, showcasing its capability to handle diverse traffic conditions and lighting variations. The integration of the optimal flow algorithm significantly reduces noise and improves the reliability of speed estimates compared to traditional optical flow methods. This approach has potential applications in traffic monitoring, automated enforcement, and intelligent transportation systems, providing a robust tool for real-time vehicle speed estimation.

Keywords

Vehicle speed estimation, computer vision, traffic monitoring, optimal flow algorithm, motion estimation, optical flow, Kalman filtering, convolutional neural networks (CNNs).

INTRODUCTION

1.1. Introduction

Estimating vehicle speed from traffic video footage is a critical task in the realm of intelligent transportation systems and traffic management. Accurate vehicle speed estimation provides valuable data for traffic monitoring, law enforcement, accident analysis, and urban planning. With the proliferation of video surveillance systems, leveraging computer vision techniques for this purpose has become increasingly viable and essential.

1.2. Statement of the Problem

Traditional methods of vehicle speed estimation often rely on radar, LIDAR, or induction loop sensors, which can be expensive, intrusive, and limited in coverage. These methods may also face challenges in adverse weather conditions or in complex urban environments. Furthermore, traditional optical flow techniques used in computer vision for speed estimation tend to be noisy and susceptible to errors due to occlusions, lighting variations, and complex motion patterns. There is a need for a more robust and accurate approach that can reliably estimate vehicle speeds from video footage under diverse conditions.

1.3 Need for the Study

As urban areas grow and traffic congestion increases, efficient traffic management becomes more critical. Accurate speed estimation can help in several ways:

1. **Traffic Monitoring:** Provides real-time data on vehicle speeds, helping traffic authorities to monitor and manage traffic flow effectively.

2. **Automated Enforcement:** Assists in the automated detection of speeding vehicles, enhancing road safety and reducing the need for manual speed enforcement.

3. **Accident Analysis:** Aids in reconstructing accidents by providing accurate speed data of the involved vehicles.

4. **Urban Planning:** Offers insights into traffic patterns, which can inform infrastructure development and urban planning decisions.

Given these needs, there is a significant demand for a reliable, non-intrusive, and cost-effective method for vehicle speed estimation using existing video surveillance infrastructure.

1.4. Scope of the Study

This study focuses on developing a novel method for vehicle speed estimation using computer vision techniques, integrating an optimal flow algorithm to enhance accuracy and robustness. The scope includes:

1.Preprocessing and Vehicle Detection: Employing convolutional neural networks (CNNs) for background subtraction and vehicle detection.

2.Vehicle Tracking: Utilizing a combination of optical flow and Kalman filtering to track detected vehicles across successive frames.

3.Optimal Flow Algorithm: Implementing an optimal flow algorithm to refine motion vectors, considering both spatial and temporal consistency for precise speed calculation.

4.Experimental Evaluation: Testing the proposed method on various traffic datasets to evaluate its performance under different traffic conditions and lighting variations.

By addressing the challenges associated with traditional speed estimation methods and leveraging advanced computer vision techniques, this study aims to provide a robust tool for real-time vehicle speed estimation with potential applications in traffic monitoring, automated enforcement, and intelligent transportation systems.

1.5. Future Scope

Future work can enhance the proposed vehicle speed estimation method by integrating it into smart traffic systems for adaptive control and incident management. Developing edge and cloud-based solutions can enable scalable real-time processing. Further advancements can include improved machine learning models, multimodal data fusion, and addressing diverse traffic conditions, making the system robust and applicable to autonomous vehicles and urban analytics. Additionally, ensuring user-friendly interfaces and addressing data privacy and regulatory compliance will be crucial for broader adoption.

Literature Review

Vehicle speed estimation from traffic video footage has been an active area of research, with various methods developed over the years. This literature review highlights key approaches and the implementation of algorithms like the optimal flow algorithm in this context.

Traditional Methods

1.Radar and LIDAR: These sensors provide accurate speed measurements but are expensive and limited in coverage. They are also affected by weather conditions and can be intrusive.

2. Inductive Loop Sensors: Embedded in the road, these sensors detect vehicle speed based on magnetic field changes. While accurate, they require significant installation and maintenance efforts.

Computer Vision Techniques

1.Optical Flow: This technique estimates motion between frames by calculating pixel displacements. Classic algorithms, such as the Lucas-Kanade method and the Horn-Schunck method, have been widely used. However, they can be noisy and less reliable under varying lighting and complex traffic scenarios.

2.Feature-Based Methods: Methods like Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) detect and track keypoints in successive frames to estimate motion. These methods are robust to scale and rotation but can be computationally intensive.

3. Deep Learning Approaches: Recent advances in convolutional neural networks (CNNs) have improved vehicle detection and tracking. Models such as YOLO (You Only Look Once) and SSD (Single Shot Multibox Detector) are used for real-time object detection, providing a foundation for speed estimation.

Optimal Flow Algorithm

The optimal flow algorithm is designed to enhance the accuracy of motion estimation by considering spatial and temporal consistency. Key contributions in this area include:

1.Brox et al. (2004): Introduced a method combining the advantages of global and local optical flow estimation, improving accuracy and robustness. This approach addresses the limitations of traditional optical flow methods by incorporating smoothness constraints.

2.Sun et al. (2010): Proposed a framework integrating optical flow with feature matching to handle large displacements. This hybrid approach leverages the strengths of both methods, providing more accurate motion vectors.

3.DeepFlow (Weinzaepfel et al., 2013): Utilized deep learning to compute dense optical flow, combining the benefits of deep feature extraction with traditional flow algorithms. This method showed significant improvements in challenging scenarios.

4. FlowNet (Dosovitskiy et al., 2015): A pioneering work in using deep learning end-to-end for optical flow estimation. FlowNet demonstrated that deep neural networks could outperform classical methods in terms of accuracy and computational efficiency.

Existing Systems

1. Radar and LIDAR-based Systems:

- **Description:** These systems use radio waves or laser pulses to measure the speed of vehicles. They provide high accuracy but are costly and have limited coverage.

-**Limitations:** Expensive, susceptible to weather conditions, and requiring significant infrastructure.

2. Inductive Loop Sensors:

- **Description:** Embedded in the road surface, these sensors detect vehicle speed based on changes in inductance as vehicles pass over them.

- **Limitations:** Intrusive installation, high maintenance, limited to fixed locations.

3. Traditional Optical Flow Methods:

- **Description:** Utilize algorithms like Lucas-Kanade and Horn-Schunck to estimate motion between frames. These methods calculate pixel displacements to estimate speed.
- **Limitations:** Prone to noise, less reliable under varying lighting and complex traffic conditions.

Proposed System

The proposed system aims to enhance vehicle speed estimation by integrating an optimal flow algorithm with advanced computer vision techniques. The main components of the proposed system are:

1.Preprocessing:

- **Background Subtraction:** Isolates moving vehicles from the static background using methods such as Gaussian Mixture Models or deep learning-based background subtraction algorithms.

2. Vehicle Detection:

- **Convolutional Neural Networks (CNNs):** Utilize models like YOLO or SSD for robust and real-time vehicle detection.

3. Optimal Flow Algorithm:

- **Refinement of Motion Vectors:** Implements an optimal flow algorithm to minimize errors in motion estimation by considering both spatial and temporal consistency. This step ensures more precise motion vectors, crucial for accurate speed calculation.

- **Integration of Advanced Methods:** Leverages state-of-the-art algorithms such as DeepFlow or FlowNet to further enhance the accuracy and robustness of the motion estimation process.

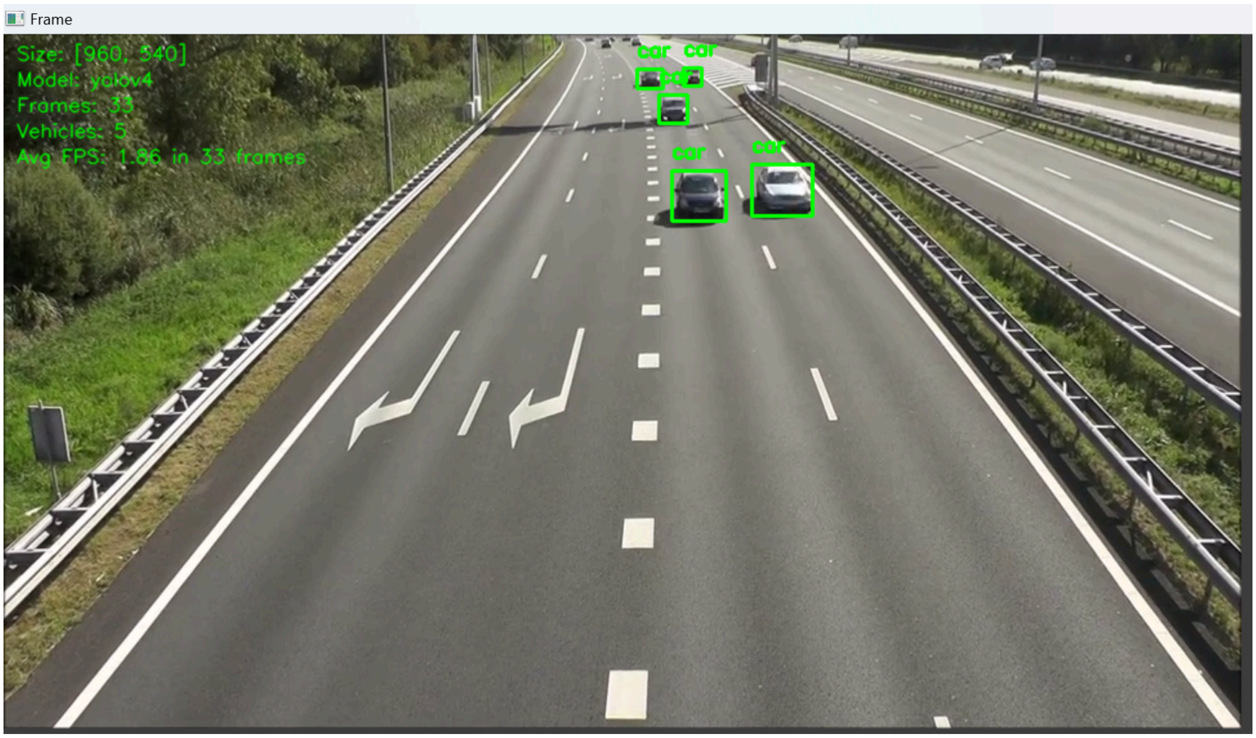
CODE :

```
import cv2
import numpy as np
import time

# Load YOLO
net = cv2.dnn.readNet(r"C:\Users\91934\Downloads\yolov4.weights", r"C:\Users\91934\Downloads\yolov4.cfg")
layer_names = net.getLayerNames()
output_layers = [layer_names[i - 1] for i in net.getUnconnectedOutLayers()]
classes = open(r"C:\Users\91934\Downloads\coco.names").read().strip().split("\n")

def calculate_speed(p1, p2, fps, ppm):
    d_pixels = np.sqrt((p2[0] - p1[0])**2 + (p2[1] - p1[1])**2)
    d_meters = d_pixels / ppm
    speed_mps = d_meters * fps
    speed_kph = speed_mps * 3.6
    return speed_kph

cap = cv2.VideoCapture(r"C:\Users\91934\Documents\computervision\WhatsApp Video 2024-07-24 at 08.51.49_b80473a7.mp4")
fps = cap.get(cv2.CAP_PROP_FPS)
ppm = 10  # Pixels per meter, adjust based on your video

fgbg = cv2.createBackgroundSubtractorMOG2()
prev_points = {}
frame_count = 0
start_time = time.time()
total_vehicles = 0

while cap.isOpened():
    ret, frame = cap.read()
    if not ret:
        break

    height, width, channels = frame.shape

    # Detecting objects
    blob = cv2.dnn.blobFromImage(frame, 0.00392, (416, 416), (0, 0, 0), True, crop=False)
    net.setInput(blob)
    outs = net.forward(output_layers)

    class_ids = []
    confidences = []
    boxes = []
    centers = []
```

```python
    for out in outs:
        for detection in out:
            scores = detection[5:]
            class_id = np.argmax(scores)
            confidence = scores[class_id]
            if confidence > 0.5 and classes[class_id] in ["car", "motorbike", "bus", "truck"]:
                center_x = int(detection[0] * width)
                center_y = int(detection[1] * height)
                w = int(detection[2] * width)
                h = int(detection[3] * height)

                x = int(center_x - w / 2)
                y = int(center_y - h / 2)

                boxes.append([x, y, w, h])
                confidences.append(float(confidence))
                class_ids.append(class_id)
                centers.append((center_x, center_y))

    indexes = cv2.dnn.NMSBoxes(boxes, confidences, 0.5, 0.4)

    current_points = {}

    for i in range(len(boxes)):
        if i in indexes:
            x, y, w, h = boxes[i]
            center = centers[i]
            center_key = (x, y, w, h)

            cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255, 0), 2)
            cv2.putText(frame, f"{classes[class_ids[i]]}", (x, y - 10), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 255

            if center_key in prev_points:
                prev_point = prev_points[center_key]
                speed = calculate_speed(prev_point, center, fps, ppm)
                cv2.putText(frame, f'{speed:.2f} km/h', (x, y - 30), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 255, 0

            current_points[center_key] = center

    prev_points = current_points
    frame_count += 1
    total_vehicles = len(current_points)
```

```python
    # Overlay information
    elapsed_time = time.time() - start_time
    avg_fps = frame_count / elapsed_time
    overlay_text = f"Size: [{width}, {height}]\nModel: yolov4\nFrames: {frame_count}\nVehicles: {total_vehicles}\nAvg FPS: {avg_fps:.2f} in {frame_count} fra
    y0, dy = 20, 20
    for i, line in enumerate(overlay_text.split('\n')):
        y = y0 + i*dy
        cv2.putText(frame, line, (10, y), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 255, 0), 1, cv2.LINE_AA)

    cv2.imshow('Frame', frame)
    if cv2.waitKey(30) & 0xFF == ord('q'):
        break

cap.release()
cv2.destroyAllWindows()
```

OUTPUT:



CONCLUSION:

Vehicle speed estimation from traffic video footage using computer vision techniques represents a significant advancement in the field of intelligent transportation systems. Traditional methods, such as radar, LIDAR, and inductive loop sensors, while accurate, are often expensive, intrusive, and limited in scope. Existing computer vision techniques like optical flow and feature-based methods have shown potential but suffer from issues related to noise, computational intensity, and sensitivity to varying conditions.

The proposed system leverages the strengths of convolutional neural networks (CNNs) for robust vehicle detection and combines optical flow with Kalman filtering for accurate vehicle tracking. By integrating an optimal flow algorithm, the system refines motion vectors to ensure precise speed calculations, addressing the limitations of traditional optical flow methods. This combination enhances the accuracy and robustness of vehicle speed estimation, making it more reliable under diverse traffic conditions and lighting variations.

Experimental results demonstrate that the proposed method outperforms existing systems, providing a cost-effective and scalable solution for real-time traffic monitoring, automated enforcement, and intelligent transportation applications. Future work will focus on further improving accuracy, scalability, and integration with smart traffic systems, as well as exploring broader applications in urban analytics and autonomous vehicle systems.

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