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Road Transport Analysis Using Neural Networks

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Abstract

This project aims to simplify the analysis of road traffic from camera recordings by enabling automatic scene annotation. Unlike manual annotation, which is labor-intensive and time-consuming, automated annotation offers a swift and data-driven solution. This accelerates the deployment of camera systems and facilitates the collection of valuable traffic data at measurement sites.

The solution involves monitoring the standard traffic conditions at the captured place. This data is crucial for subsequent real-time traffic control. By employing multiple object tracking, the system extracts the trajectories of moving objects. Afterward, the DBSCAN clustering algorithm is applied to these trajectories to identify dominant vehicle movement patterns. These groups are then visually represented in the scene and utilized for further statistical analysis.

The system's capability to determine various vehicle streams is based on the correctness of object detection and tracking. Although measures have been put in place to verify the data, issues such as false positives and tracking errors can still undermine overall performance.

This method represents a novel approach to automating camera system settings. Its independence from road signs and camera positioning significantly enhances its utility for traffic camera deployment.

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1. Introduction

[Motivation]

The motivation for this project arises from the need to deploy new traffic cameras faster. Traditional traffic cameras need manual settings or more sensors for calibration. The proposed automated camera system addresses these challenges by enabling rapid deployment and reducing reliance on manual labor. Using advanced algorithms for object detection and tracking, this system delivers automated annotations, backed by data, which can be used to optimize the traffic or used in real-time surveillance for anomaly control.

[Problem definition] The primary challenge lies in identifying specific lanes and vehicle movement directions within captured scenes to detect anomalies such as vehicles driving in the opposite direction or making illegal U-turns. Traditionally, this task was handled by human annotators or monitoring systems that combined multiple sensors. The proposed solution is capable of annotating the scene only using static camera input.

[Existing solutions] An existing solution, Automatic Camera Calibration for Traffic Understanding [1], primarily calculates vehicle volumes and speeds. In contrast, the proposed system concentrates on the direction of vehicle movement. Unlike [1], which estimates speed based on vehicle scale, our approach focuses on groups of vehicles and identifies those that traverse their trajectory distance significantly faster than others.

[Proposed solution] This solution operates independently of traffic signs, lanes, or other markings. Instead, it relies on the duration and quality of data collection. More comprehensive data collection periods lead to more accurate and reliable analysis results.

[Contributions] This introduces a novel approach to processing data obtained from object tracking for traffic analysis. The method also holds potential for other applications where it is necessary to automatically identify the primary movement patterns of multiple objects over a given period.

2. System design

[Collecting of trajectories] To detect vehicles in captured scenes, it's necessary to either train a vehicle detector or use a pre-trained model. I initially experimented with the YOLOv8n [2], pre-trained on the COCO dataset. While this model was not particularly accurate for detecting different types of vehicles, it proved effective for identifying unusual objects in the scene. Subsequently, I developed a custom vehicle dataset from publicly available videos, comprising over 6000 annotations across five vehicle classes. The detector trained on this custom dataset significantly improved the accuracy of our statistics and reduced the incidence of false detections associated with the COCO-trained model.

YOLOv8 supports the ByteTrack and BoTSORT tracking algorithms. For our solution, BoTSORT was chosen due to its integrated global motion compensation, which is crucial for cameras mounted on non-static platforms.

Despite the detector being specifically trained on vehicle data and the tracking algorithm being highly advanced, there can still be inaccuracies, such as ID switches or occlusions by barriers. These issues may result in incomplete trajectories that offer little directional information. Such trajectories are filtered out. For the remaining valid trajectories, a consistent proportion of coordinates is extracted from each, enabling effective clustering.

[Clustering] Clustering automatically groups collected data based on the similarity of their trajectories, a task typically performed manually. Due to the uncertainty regarding the number of vehicle streams in a new scene, algorithms like K-means, which require predefined cluster numbers, are unsuitable. Additionally, the nature of the data does not fit well with hierarchical clustering. Therefore, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) was chosen. The epsilon parameter for DBSCAN is determined from a K-nearest neighbors graph, while the minimum number of points is set at the lower of the trajectory dimension (number of coordinates) or a fraction of the total data. We cap the clusters at twelve for a four-way junction to manage complexity and ensure meaningful analysis.

[Automatic scene annotation]This approach automatically segments the data into distinct streams. Using this segmentation, we can annotate the scene by marking the mean of each cluster as the primary reference trajectory and the boundaries of the cluster as border points.

[Statistics and detection of anomalies]This method establishes a baseline for typical conditions at the traffic site, including the usual number and type of vehicles per lane, as well as standard trajectories and transit times. Using this baseline, we can detect abnormal traffic behaviors potentially caused by accidents or road obstacles.

Furthermore, anomalies within the clusters, such as unusually fast traversal of a trajectory suggesting speeding, or atypical cases like a car in a bus lane, can also be identified.

3. Conclusions

The objective of this project was to develop a system for analyzing road traffic, emphasizing its automatic configuration. This goal has been successfully achieved additionally the method was embedded into commercial traffic camera software. While the system's results depend significantly on the quality of the data collected, it proves valuable when integrated with other methods, such as image segmentation for identifying road surfaces, or data from additional sensors like radars.

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