Technische Universität München

Automatic Detection of Traffic Streams with Machine Vision

Master‘s Thesis of Mohammed Zubair

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Introduction

Due to the increasing traffic and its implications, the demand for accurate and reliable traffic data has become crucial, leading to significant advancements in methods and analysis techniques. Video-based traffic data collection offers numerous advantages, such as portable camera installation, enabling applications like vehicle behavior analysis, traffic counting, including non-vehicular traffic, violation detection, congestion monitoring, safety analysis, and non-vehicular traffic observations, establishing it as an indispensable tool in the field.

Addressing the limitations of manual counts, deep learning algorithms have been incorporated to aid real-time detection. Advancements in vehicle detection, including CNN and R-CNN, have ushered in progress but have also produced challenges. These include adapting to various scenarios, tackling occlusions, and the complexities of determining vehicle trajectories at intersections. Amid this evolving landscape, a noticeable research gap persists.

While modern video-based systems excel at vehicle detection, their practicality in automating vehicle counts and detecting traffic streams remains largely unexplored. This study aimed to devise an adaptable concept for automated traffic stream detection across vehicle classes, balancing practicality and accuracy in vehicle counting. The objective is an adaptive system that automatically detects and clusters traffic flows, catering to varied urban scenarios. The research focused on achieving both precision and adaptability in algorithm design for evolving urban traffic patterns.

Methodology

22 locations were strategically selected based on geography, camera views, intersection types, complexity, and traffic volume. Centroid-based clustering algorithms such as K-Means and K-Medoids, as well as density-based ones like DBSCAN and OPTICS were explored. Various similarity functions, including Hausdorff distance and Longest Common Subsequence (LCSS), were evaluated alongside these algorithms.

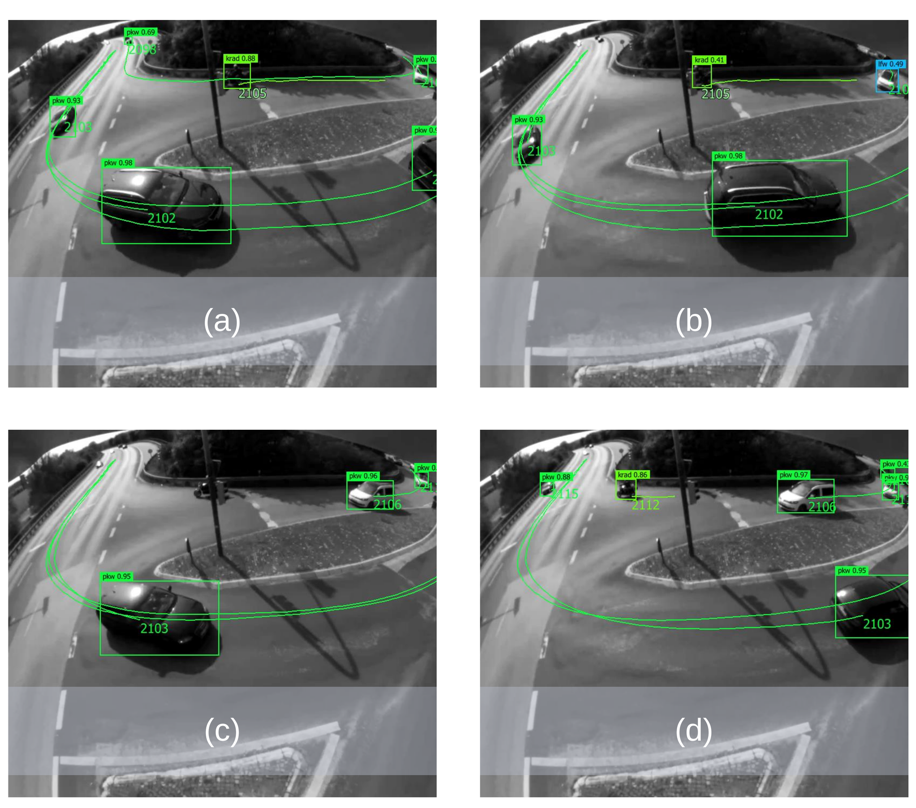

Figure 1: Object - background occlusion: A dip in *CONFIDENCE* for trajectory ID 2105 from 0.88 to 0.41 (b), followed by non-detection (c), and emergence of new trajectory ID 2112 (d) - retrieved from mouver GmbH

Results - Visualized

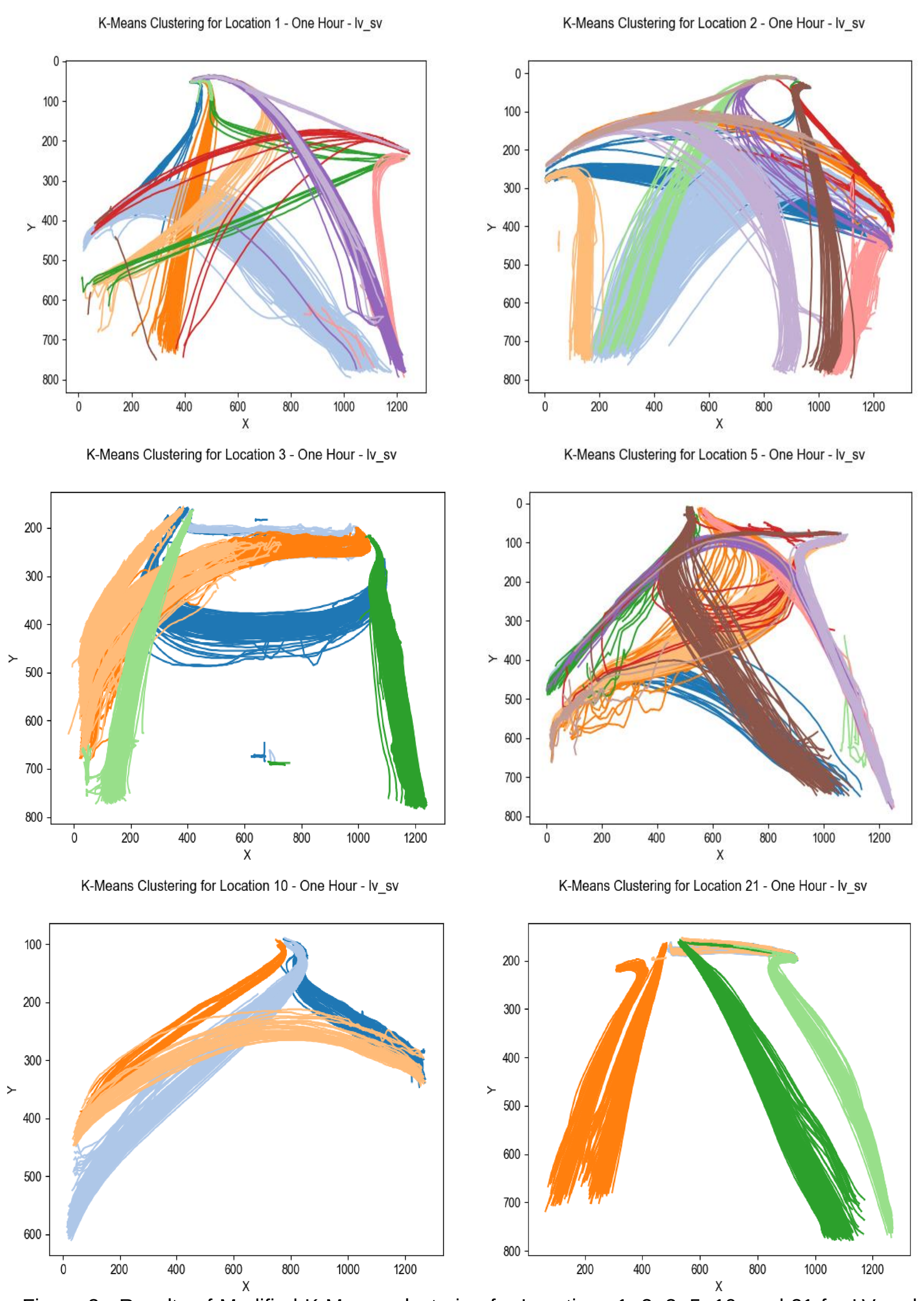

Figure 2: Results of Modified K-Means clustering for Locations 1, 2, 3, 5, 10, and 21 for LV and SV one hour data

The *CONFIDENCE* values for SV, Rad, and Fuss averaged 0.711, 0.687, and 0.593, lower than LV's 0.839; thus, the study focused on clustering motorized vehicles, specifically LV and combined LV with SV.

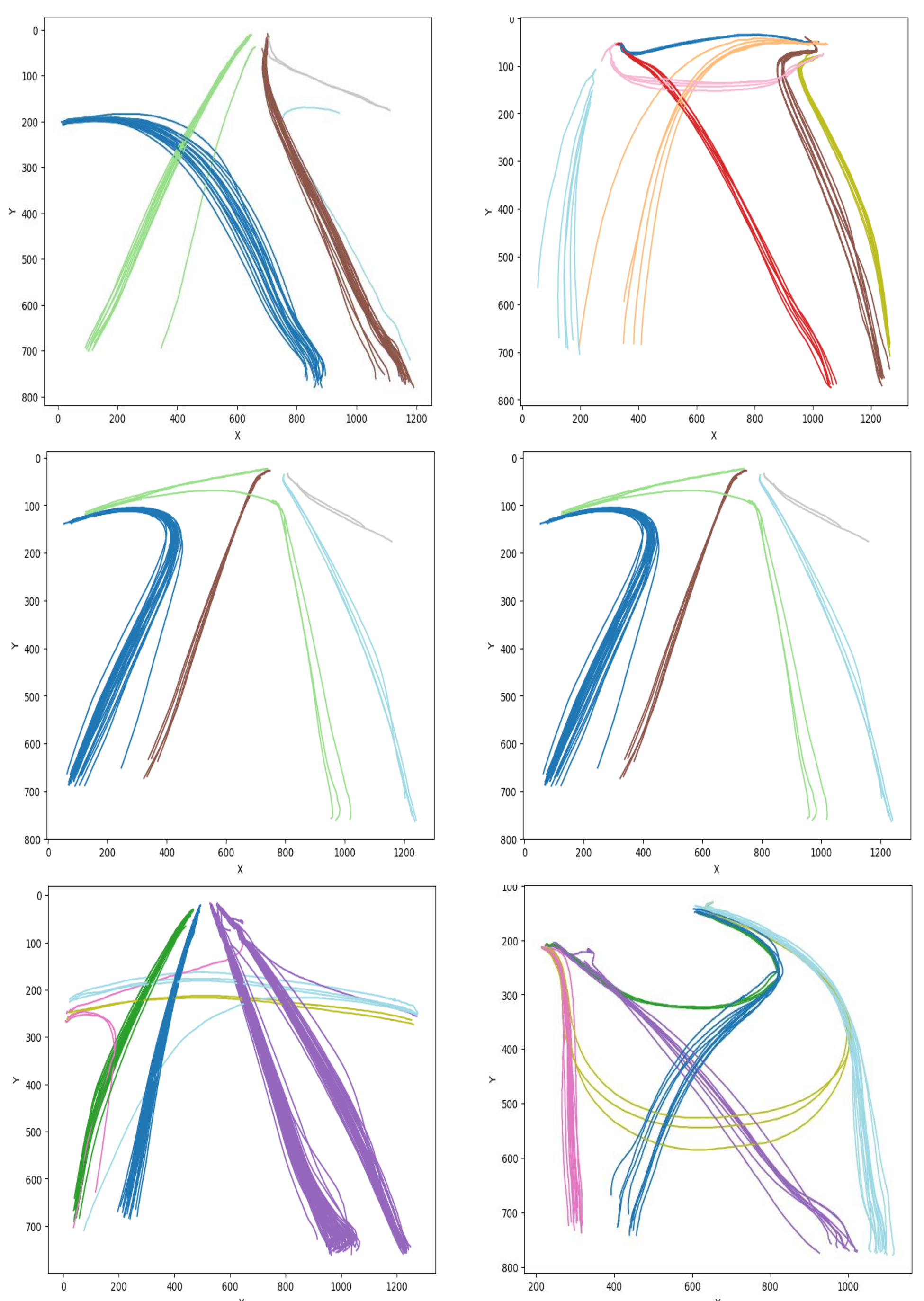

Figure 3: Results of further testing on OPTICS with LCSS distance metric

Results and Discussion

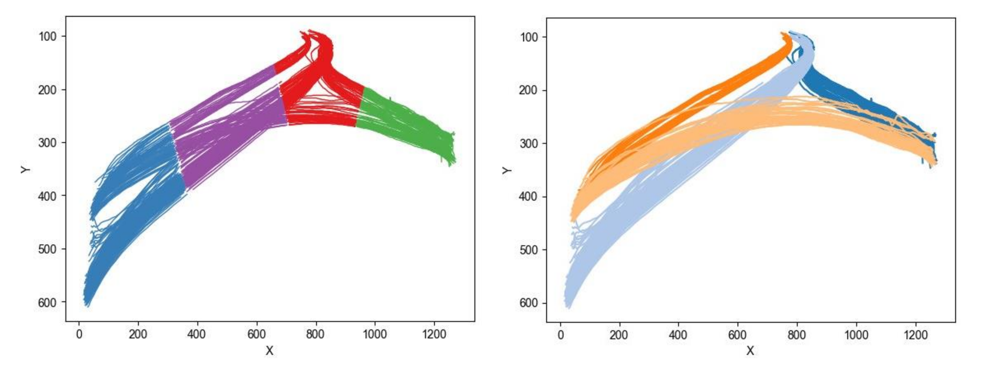

Figure 4: Left: Initial K-Means displays multi-cluster trajectories, indicating clustering ambiguity. Right: Modified K-Means for one-hour trajectories at Location 10 uses a three-point direction method.

In a comprehensive study across six selected locations, the dataset was partitioned into 5-minute, 15-minute, and 1-hour segments to accommodate the computational limitations of clustering algorithms. To enhance clustering in OPTICS LCSS, the minimum sample value was adjusted from 1 (which consolidated all data into one cluster) to 2. The study journeyed from direct K-Means, which scattered trajectories among multiple clusters, to a refined iteration focused on single-cluster mapping. The evolution continued with an average point strategy, culminating in Modified K-Means that employed average, start, and end points to accentuate differentiation. This algorithm exhibited varying accuracies, excelling in scenarios devoid of outliers but encountering challenges like cluster fragmentation, occlusions, and overestimations in complex scenarios. K-Medoids Hausdorff struggled with trajectory overlaps at densely populated intersections, while OPTICS paired with Hausdorff consistently underperformed compared to other metrics. The crux in OPTICS LCSS was the epsilon (eps) value: too low led to fragmented clusters, while too high prompted over-aggregation, underlining the importance of optimization and validation.

When gauged for computation time, Modified K-Means and K-Medoids Hausdorff outpaced OPTICS derivatives, with OPTICS LCSS being notably slow. Overall, the Modified K-Means stood out for its resilience across diverse locales, especially in minimally occluded areas. However, occlusions remained its drawback. The OPTICS variants, particularly with LCSS and epsilon values of 20 and 40, showed promise, but their success hinged profoundly on the choice of eps. The study underlined a consistent theme: the integrity of the data was pivotal to the proficiency of clustering approaches.

Summary and Outlook

While recent advancements in video-based vehicle detection systems have enhanced vehicle detection accuracy, real-world vehicle counting remains a challenge. This study aimed to cluster vehicle trajectories, which often overlap and vary based on vehicle type, further complicated by erratic traffic patterns. While OPTICS with LCSS yielded accurate yet computationally expensive results, Modified K-means was more efficient but less precise. Future research aims to create a similarity function with the area-under-the-curve method for a practical and an efficient system that is independent of epsilon values.

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- CNN and R-CNN – Convolutional Neural Network and Region Convolutional Neural Network
- *CONFIDENCE* - Indicates the neural network’s level of certainty in its vehicle detection for the frame in question. These floating-point values range from 0 to 1, where higher values signify a higher level of confidence in the vehicle’s detection.
- SV – Schwerverkehr (Heavy Vehicle)
- LV – Leichtverkehr (Light Vehicle)
- Rad – Radfahrer (Cyclist)
- Fuss – Fußgänger (Pedestrian)