On the Impact of Classification Quality of Multiple Object Tracking Systems on Analysing the Path Choice Behaviour of Multimodal Traffic

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Abstract. Multiple object tracking (MOT) systems are increasingly used for acquiring comprehensive motion data relevant to many fields of traffic research. Due to an increased interest in multi-modal traffic, the ability of such systems to distinguish between different object classes is a relevant quality criterion. This work discusses different aspects of classification quality and analyses the quality of two classifying systems at the same intersection in a comparative manner. Preliminary results show that the classification might be challenging for behaviour analysis and approaches to address the challenges are discussed.

Keywords. Traffic Trajectories, Multiple Object Tracking, Object Classification, Behaviour Analysis

1. Introduction

Multiple object tracking (MOT) systems are increasingly used for acquiring comprehensive motion data relevant to many fields of traffic research (Jiménez-Bravo et al. 2022). Their ability to track every object in a particular location allows the resulting trajectory data to be used for comprehensive analyses of traffic participants' behaviour (Yuan et al. 2019), for the calibration of microscopic models (Zhao, Knoop, and Wang 2023), for infrastructure supported collision warning systems (Liu, Muramatsu, and Okubo 2018) and for digital twins (Wang et al. 2022). While early research was mainly focused on motorized vehicles, attention is increasingly given to multi-modal traffic. Especially vulnerable road users and their interaction with other vehicles are of great interest. Hence, MOT systems are required to reliably classify different types of traffic participants.

As part of our current research, we investigate methods to assess the classification quality of MOT systems while treating the generating system as a

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black box and methods to meaningfully analyse the path choice behaviour of multi-modal traffic in the presence of imperfect classification. In this work, we discuss different aspects of classification quality. We then present preliminary findings from comparatively analysing the classifications of a LiDAR-based MOT system and an optical classifier. We conclude this work by a discussion of the findings, their implications for path choice analysis, and the path choice analysis approach we are currently investigating.

2. Different Aspects of Classification Quality

The classification accuracy, i.e., the percentage of objects that the system assigns the correct class to, is a relevant quality criterion of MOT systems (Luiten et al. 2021). Additionally, the granularity of classification, i.e., the number of object classes that the system can distinguish, should be considered. A system that classifies objects into less classes might achieve a higher accuracy than a system that distinguishes more classes, but its resulting classifications might be less valuable for applications as objects with different characteristics might be combined in one class. Especially different groups of vulnerable road users can be difficult to distinguish, e.g., pedestrians, pedestrians pushing their bicycle or a baby stroller, and riders of bicycles, electric bicycles, electric scooters or different types of motorized two-wheelers. However, distinguishing these traffic participants is of great interest when analysing their behaviour.

In the case of MOT systems that operate in real-time, the stability of object classification is another quality criterion. Such systems can only use information up to the time of calculation and future information might change the classification of an object. An additional processing step is then required to decide on the final classification of an object when it is ambiguous.

3. Experiments

As a testbed for our research, we use an intersection in the City of Salzburg located at 13.0642° longitude, 47.8097° latitude. Six LiDAR sensors (31° vertical field of view at 1° resolution, 360° horizontal field of view at 0.18° horizontal resolution at 10 Hz) and a state-of-the-art perception software running at the roadside are used to detect, track the movement of, and classify traffic participants. This LiDAR-based system (LS) continuously sends time-referenced object positions and additional object attributes with a frequency of 10Hz to a server that assembles the single object measurements to object trajectories. The real-time characteristic of the LS causes classification to vary within a trajectory. Additionally, the intersection is equipped with four optical systems (OS) for detecting and classifying traffic participants. While the LS is designed to track objects through the whole intersection, each OS is focused on a specific area aiming at a reliable detection and classification there. To analyse the classifications of both systems, we fuse the classifications from one OS with LS object trajectories using spatio-temporal information. As a result, every trajectory that intersects the classification zone of the OS gets an additional classification. The layout of the intersection and the position of sensors relevant to the experiments are shown in Figure 1.

The following findings are based on data from a two-hour period in which the OS detected 718 cars, 37 trucks, 10 buses, 24 motorbikes, and 37 bicycles. The LS can distinguish vehicles, two-wheelers, and pedestrians. Table 1 compares the classification of objects between the LS and the OS.

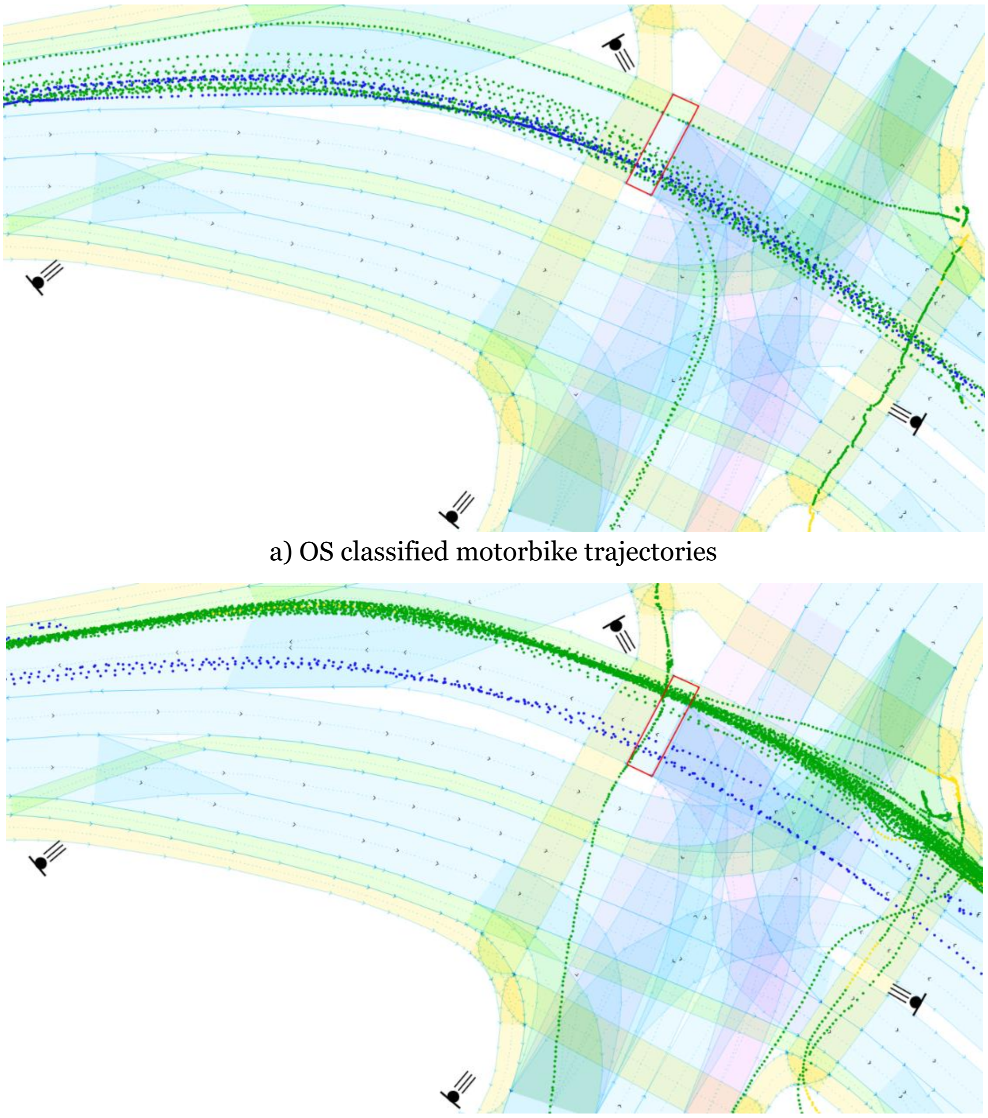
OS\LS	% vehicle	% two-wheeler	% pedestrian	% unclassified	total
truck	94.6	5.4	0	0	37
bus	90.0	0	0	10.0	10
car	99.3	0.4	0	0.3	718
motorbike	29.2	70.8	0	0	24
bicycle	10.8	86.5	0	2.7	37

Table 1. Percentages of LS object classes in terms of the most frequent classification per trajectory for each OS object class.

Additionally, we visualize the trajectories of each OS class for further analysis. Bicycle and motorbike trajectories are shown in Figure 1. We find that the LS classifies both OS motorbikes and OS bicycles mostly as two-wheelers and sometimes as vehicles. Some objects are classified as pedestrian momentarily, but the classification of all objects is stable enough to be unambiguous. The presence of a dedicated bicycle lane and the speed of the objects provide further indication on the classification accuracy of the systems. One OS motorbike is slowly driving on the bicycle lane after it used the zebra crossing where it also was classified as pedestrian by the LS. This could be a cyclist that pushed his bike over the crossing and then started riding. Several OS bicycles are classified as vehicle by the LS and do not use the dedicated lane.

4. Discussion

Mostly, the two systems' classifications are in correspondence. Objects classified as cars by the OS are seen as vehicles by the LS very consistently. However, OS classified motorbikes and bicycles are sometimes classified as vehicle by the LS. The granularity of the LS classification is challenging for further analyses, as it does not distinguish between bicycles and motorized two-wheelers. Fusing trajectories with OS classifications allows for that distinction, but a subclassification is not implemented either. While a subclassification of vehicles into cars, busses and trucks is common, classifying different types of bicycles, e.g., cargo or electrical bicycles, is still challenging.



a) OS classified motorbike trajectories

b) OS classified bicycle trajectories

Figure 1. LS trajectories of objects that have been classified as motorbike (a) and bicycle (b) in the red quadrangle by the OS. Point colour indicates the LS classification (blue = vehicle, green = two-wheeler, yellow = pedestrian). Coloured areas correspond to vehicle lanes (blue), bicycle lanes (green), walkways (yellow), and bus lanes (pink). Black symbols indicate the positions of LiDAR sensors.

Additionally, the accuracy of classifications is in question considering the paths of trajectories. For a concrete evaluation, ground truth information is necessary. A reclassification of objects using features derived from attributes such as speed, size, and lane choices might improve accuracy. Supervised learning with manual classifications as targets could implement this. However, using such features for a reclassification will bias analyses. For example, if the position on or off the cycle lane is utilized to distinguish motorbikes from bicycles, further behaviour analyses cannot reliably investigate how many cyclists do not use the cycle lane, as such objects would not be classified as cyclists. Hence, classification should be based on the shape of objects alone. In the presence of imperfect classification, behaviour analysis should follow an approach that does not rely heavily on a detailed and accurate classification. To this end, we look into trajectory clustering as a method to detect different path choices of traffic participants crossing the intersection from one particular side to another. This way, the focus is on the paths taken to cross the intersection. Then, we can analyse each cluster of trajectories with respect to various features, including object classes, that might explain the path choice. Consequently, we get an idea which objects (and in which situations) tend to use a certain path. First experiments show promising results.

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