Towards Corner Case Identification in Cyclists' Trajectories

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ABSTRACT

In this article, we present an idea for corner case identification in cyclists' trajectories. The ability to identify corner cases is vital for verification and validation of machine learning methods, especially in the domain of ensuring automated driving functions. Corner cases usually consist of critical situation, so their number is very small and therefore difficult to find in a vast of data. In this article, we focus on cyclists' trajectories used for the training of machine learning-based intention detection models. The method starts with a transformation of a cyclists' trajectory in a position and orientation independent coordinate system. Afterward, we use the coefficients of an orthogonal polynomial approximation to describe the cyclist's trajectory in a compact but yet expressive way. Based on the coefficients of these polynomials, we aim to identify critical and also uncommon trajectories in the data. Therefore, we apply a density-based model as well as novelty detection. The idea of our approach should be transferable as far as possible to other vulnerable road users such as pedestrians.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; **Machine learning**; • **Applied computing**;

KEYWORDS

corner case, data aquisition, cyclist trajectory, intention detection, trajectory prediction, machine learning

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1 INTRODUCTION

A car driver drives along a road. Suddenly, behind a parked truck, a person steps onto the road. The driver can prevent the accident because she has already reduced her speed due to years of experience. In the future, autonomous vehicles will have to deal with such critical and unpredictable situations as well. The development of machine learning algorithms for pedestrians or in general for vulnerable road user intention detection [2], prediction, and situation analysis is one major aspect in ensuring automated driving functions. For this purpose, data for training and testing of the machine learning methods is required and has to be collected. However, the provision of representative sensor data for such complex learning processes is still an open problem. The difficulty lies in the fact that critical and thus, serious situations are particularly rare and often hidden in a vast amount of uninteresting data. The identification of these critical but rare situations, also referred to as *corner cases* [3], is crucial for testing and validating machine learning-based intention detection models. In this article, we introduce a novel methodology to recognize corner case data in trajectory datasets. To further motivate our approach, consider the following scenario recorded an urban intersection [8] as depicted in Fig. 1. In this case, cyclists usually come from the bottom right then drive straight through the scene or crosses the road via the pedestrian crossing. These common trajectories are drawn in gray. However, in this particular case, a cyclist

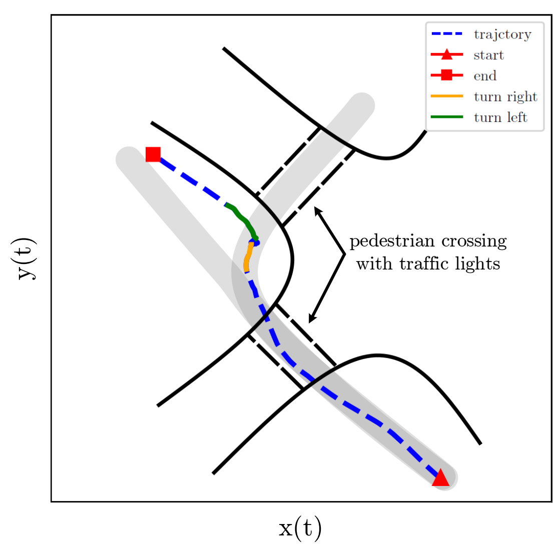

Figure 1: The figure shows a schematic drawing of the crossing, the common trajectory paths (gray) and an uncommon trajectory sequence, where a cyclist (dashed blue line) instead of crossing the road continues along the road.

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(dashed blue line) arrives at the pedestrian crossing. Initially, it looks like she intends to cross the street, but she changed her mind and heads along the other direction. This trajectory is a typical uncommon and potentially critical situation, e.g. an approaching vehicle might need to brake firmly to avoid a collision with the crossing cyclist, potentially leading to rear-end collision with another car. In this article, we aim to identify such uncommon situations and distinguish them from the vast amount of usual trajectory data.
The remainder of this article is structured as follows. In Section 2, we describe the first approaches for corner case identification. Finally, a conclusion and outlook to future work are given in Section 3.

2 CORNER CASE IDENTIFICATION

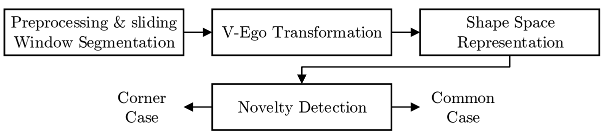

Figure 2: Pipeline towards corner case identification.

Our concept for the identification of corner cases in cyclist trajectory data essentially consists of the four blocks shown in Fig. 2. We represent each trajectory by a time series consisting of a two-dimensional position indication $(X_0, ..., X_k)$ at k discrete, usually equidistant points in time. For preprocessing, e.g. filtering, we apply similar techniques as described in [1]. Subsequently, we use a sliding window segmentation to obtain a location and orientation independent representation of the considered trajectory segment. Therefore we transform the trajectory from the world coordinate system into the ego coordinate system of the cyclist [7]. In this ego coordinate system, all movements are mapped independently of the global location or direction. The transformation into this coordinate system is done by translating the current position into the origin of the coordinate system and rotating it by the negative, horizontal angle of the current direction of motion, so that the new horizontal coordinate axes are aligned (longitudinal) and perpendicular (lateral) to the direction of motion. We represent the transformed trajectory using the coefficients of the orthogonal polynomial approximation of the respective trajectory. The polynomial coefficients are in a least-square sense best estimation of the mean, slope, and curvature of the input signal [5]. This representation is also referred to as shape space [4, 6]. Currently, we use polynomials up to the 4th degree. However, a clear statement on the degree of the polynomial cannot be given at the current stage of development, because the degree has a significant influence on how much information is lost if the degree is to small or rather kept if the degree is large enough. With this procedure, we end up with two orthogonal polynomials one for the x-coordinate and one for the y-coordinate over the time t. The last step is to identify and classify the coefficients of orthogonal polynomials to find the relevant sequences containing the corner cases [9]. To accomplish this task, we use density-based modeling techniques, and novelty detection methods. A suitable method would be CANDIES [10], a method based on a probabilistic model in this case a Gaussian Mixture Model and has two main focuses. The first is to detect novelty accumulations in so-called low density regions (LDR), i.e. regions where no regular samples are expected. The second focus is on high density regions (HDR), i.e. regions where the novelties are hidden by regular samples. Depending on whether the new sample is in the LDR or HDR region, appropriate detectors are used to check in case the sample is a novelty or in our case a corner case. This knowledge can now be taken into account by the model, which makes our corner case a well known case.

3 CONCLUSION

In this article, we have proposed a novel method to identify corner cases in trajectory data. With the described method, we do aim to find corner cases efficiently. Moreover, we want to investigate what our proposed method detects as unusual or even critical. In return, we also hope to gain insights into how trajectories are classified as critical by humans and how this relates to our corner case identification method. Our idea and implementation so far is mainly focused on cyclists' trajectories, but for future work, we also apply these ideas to other trajectory datasets, e.g. pedestrians and other vulnerable road users.

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