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Applications of AI in Transportation Industry

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Abstract

This introductory article opens the section on "Applications of AI in Transportation Industry", giving a broad overview of the latest AI technologies in the transportation industry, with an additional focus on the developments enabling automated Mobility-as-a-Service (MaaS). It presents future capabilities and opportunities for AI, together with covering state-of-the-art Intelligent Transport Systems (ITS) trends, including advancements on the vehicle, infrastructure, and management level. Finally, the article outlines the two papers included in this section, highlighting concepts and challenges of using AI for automated, optimised, and individual passenger transport.

Keywords: intelligent transport systems (ITS), mobility-as-a-service (MaaS), advanced driver assistance systems (ADAS).

5.0.1 Introduction and Background

Transportation industry is a crucial element to guarantee our daily lives. Following the previous trends of the last decade, the transportation industry has pioneered by digitising its processes by introducing extensive data systems and automated agents, spanning from the vehicle up to traffic systems.

To understand and control this data, it became mandatory to optimise processes on the micro- and macroscopic level in this complex, ever-changing ecosystem. However, since data alone does not enable higher efficiency, safety or automation, the demand for data processing is constantly increasing. Thereby, specific use cases, e.g., in the field of automated driving, require high demands in terms of latency. Decentralised, intelligent systems leveraging efficient AI models and suitable edge computation platforms are currently being investigated to close the gap. These developments will contribute to the European Commission long-term strategies "*Vision Zero*" (reduce road fatalities to almost zero) and "*European Green Deal*" (climate-neutrality), which should be reached by 2050.

In this introduction article, we will introduce the state-of-the-art for automated passenger transport. Thereby, we will elaborate on recent trends on AI-enabled automated MaaS in the field of ITS and envision possible opportunities. Finally, the article outlines ongoing activities concerning the *AI4DI* project that are presented in two separate articles.

5.0.2 AI Developments in Transportation Industry

In recent years, AI progressively became an imperative approach for processing ITS related data. This trend, reinforced by wide industrial support, establishes a solid foundation to build an efficient MaaS architecture. Accordingly, the latest progress for Machine Learning (ML) applications is discussed based on the survey by Yuan et al. [1]. The authors of this paper structure ML applications in three primary tasks: perception, prediction, and management. This differentiation corresponds to the processing architecture for automated driving, namely perception, planning, and control, which by itself is an expansive research field [2] [3].

Perception – Nowadays, due to the broad usage of different sensors such as cameras, LiDARs, and radars, traffic perception data's variety and quantity increased exponentially. Accordingly, ML approaches are progressively leveraged as a first step to process this data to retrieve valuable information. Perception aspects deal with the physical world (road, vehicles, and pedestrians) and the monitoring of the digital components (reliability and security of the communication network).

Whereas earlier work for object classification, detection, and segmentation leverages mainly supervised ML algorithms such as Support Vector Machines (SVM) utilising hand-crafted features, recent trends aim to harness deep-learning (DL) models, capable of embedding features in their neural network architecture. Common approaches include Convolutional Neural Network (CNN), and implementations such as YoloV4 [4]. In contrast to traditional algorithms, these models tend to be more versatile (resolution, orientation, scene) and robust against anomalies or external conditions (daylight or weather). Besides perception algorithms relying on a single sensor-type input, data-fusion approaches are currently under development. These operate either low-level (a single model uses all raw sensor inputs for inference) or high-level (multiple networks are used, and outputs are concatenated at a later stage) [5] and further improve the overall reliability of the perception module. Moreover, perception algorithms fusing the output of multiple agents generating HD-maps and digital twins [6] are research fields.

Prediction – Diverse ML approaches are investigated for ITS to fulfil prediction purposes, including anticipating traffic, travel times, vehicle behaviour, and road occupancy. These methods improve the decision-making fleet management, e.g., regarding the last mile support use case. Traffic flow prediction methods are applied based on the results of the presented perception models and are used to determine travel times for vehicles and passengers. Subsequently, the results are leveraged to eventually optimise the vehicle and route selection on a global scale. Since these tasks require the model of temporal-spatial changes, Recurrent Neural Network (RNN) architectures and derivates, such as Long Short-Term Memory (LSTM) [7], are employed.

Management – ML for management tasks is considered to raise efficiency on vehicle-, infrastructure-, and resource-level. This includes control of traffic lights and a trajectory or route selection for the automated fleet. Secondary tasks, such as networking and computation problems, are tackled, comprising resource management for V2X communication [8] and mobility-aware edge computing offloading [9].

In contrast to the previous domain, ML often investigates deep reinforcement learning (DRL) techniques for management decisions. For instance, Deep Q-Learning (DQN) is considered to optimise traffic light management to minimise queue waiting times [10]. Besides, Proximal

Policy Optimization (PPO) is leveraged for steering and speed control of an automated vehicle [11].

5.0.3 Future Trends for Applications in Transportation Industry

The following paragraphs elaborate on two future applications utilising the introduced ML technologies in detail.

Automated driving – In recent years, AI has been used commercially in passenger cars' Advanced Driver Assistance Systems (ADAS). In addition, lately, AI has also been used in the development of automated driving functionalities. CNN and DRL are the most common deep learning methodologies, which have been successfully applied to automated driving solutions. Developing a reliable and robust fully Automated Driving System (ADS) often needs that several AI methods are used together.

Training data is one of the essential requirements and challenges to develop deep learning solutions. Many ADS developers have done the collection of large data sets for autonomous driving and environment perception. Luckily, more and more open data sets have been published for the research community. One of the best-recognized data sets for ADS development is the KITTI benchmark suite [12], which includes several data sets to evaluate various ADS functions [3]. There are also other similar open data sets such as Waymo Open data set [13], Cityscapes [14], Berkeley DeepDrive [15], etc. The training data is always limited as it is impossible to cover all scenarios that an automated vehicle could encounter in the real world. However, the rapid progress in collecting larger and larger data sets will enable more advanced deep learning systems on automated vehicles.

The environment perception and scene understanding around the vehicle is crucial for automated driving. This includes detection of other road users, road markings and other road furniture. Deep neural networks, such as CNNs, are today very accurate for detecting, tracking, and classifying various road user types, including cars, trucks, busses, pedestrians, cyclists, etc. A breakthrough has been achieved in pedestrian detection solutions with deep learning [1]. However, there are still some challenges in the pedestrian detection task from camera data, such as substantial occlusions and bad weather conditions. Deep learning-based methods are also widely used for detecting and tracking positions and geometries of moving obstacles (e.g., other vehicles) based on camera data [16]. Image segmentation is used to classify the pixels of an image into the road and non-road parts [1]. Road marking detection and recognition involves detecting the marking positions and recognizing their types (e.g., lane markings, road markings, messages, and crosswalks) [16]. Other road furniture detection includes, for example, traffic sign recognition.

AI-based environment perception algorithms utilize only two dimensions (2D). However, 2D models are not enough in all cases to describe 3D real-world objects. The 3D perception is based on LiDAR or stereo cameras. 3D tracking and behaviour prediction of other road users is required in automated driving. Vehicle behaviour corresponds to braking, steering, lane change and moving trajectory [1]. Pedestrian behaviour includes actions like running or crossing the street [1]. In future years, AI and ML will gradually enable better prediction of the behaviour and intent of other road users.

Traffic flow and public transport travel time prediction – Various combinations of AI algorithms have been used in predicting traffic flow and travel time. Travel time predictions enable, for example for vehicle routing, guide vehicle dispatching, as well as congestion and traffic management. Forecasting traffic flows and travel time is a complex and challenging problem, which is affected by diverse factors, including spatial correlations, temporal dependencies, and external conditions (e.g., events, holidays, weather, and traffic lights) [1]. For travel time prediction, there are segment and path-based estimation approaches. Lately, integrated DL methods, which utilize both segment-based and path-based approaches, have also been studied. Recently researchers have also combined deep learning with traditional methods with some success [1].

One problem with AI-based prediction development is that training data is not readily available as most road networks are not equipped with traffic measurement sensors. Traffic data can be collected from mobile devices, and this data is often available from global map data providers such as Google or Here. In many cases, multiple data sources are used together to get better results. High-quality public data sets from the real-world are essential for accurate traffic forecasting. These are progressively available from some cities in Europe as open public data. For example, the open public transport data from a city may provide many opportunities to develop new AI-based tools. Today, most public transport vehicles are fitted with positioning systems (e.g., Global Navigation Satellite System - GNSS), which provides accurate real-time information about the current location and movements of the vehicles. Typically, open public transport data from a city includes vehicle

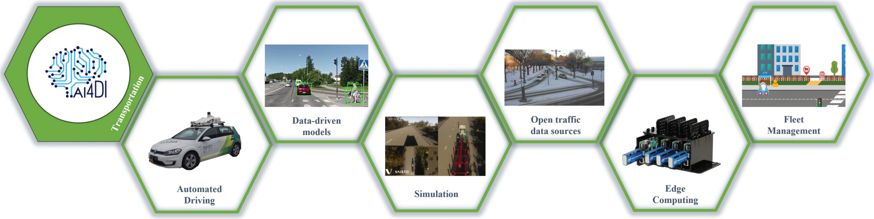

Figure 5.0.1 Transportation research areas in AI4DI.

positions, public transport schedules and route identifiers, etc. This kind of continuous open data stream has enabled the development of Estimated Times of Arrival (ETA) prediction methods utilising ML. Recently, in many studies, several external data sources such as weather, traffic and information about the passengers have been combined for machine learning model development [17].

5.0.4 AI-Based Applications

AI4DI partners are developing AI and Industrial Internet of Things (IIoT) technologies with applications in different areas of the transportation industry sector. This section introduces two articles covering how AI and IIoT are used in the transportation sector. They present challenges and technological developments for perception, prediction, and management in the context of automated MaaS.

The article "*AI-Based Vehicle Systems for Mobility-as-a-Service Application*" describes the safe operation of automated vehicles in urban environments, attempting to improve the environmental perception to detect other road users by proposing a novel method for data fusion between an in-vehicle camera and a LiDAR sensor. Accurate 3D object detection and tracking is achieved by employing deep models (high-level, deterministic, supervised, and reinforcement learning). The KITTI benchmark suite has been used for development and validation, with promising results. The gap between simulated and real environments continuously diminishes with the rapid advances in autonomous control technology that offer improved visual and physical experiences.

The article "*Open Traffic Data for Mobility-as-a-Service Applications - Architecture and Challenges*" addresses the need for high-quality public data sets from the real world with advancing digitisation in the domain of ITS and hence the need for data pre-processing from multiple sources, including raw sensor data, to prepare for AI-based modelling. While current pre-processing is often implemented as a cloud solution, a system architecture is proposed where computations are scaled and distributed to different layers in the edge–cloud continuum. A set of data refinement strategies has been developed to improve data quality and integrity, which refine the data into becoming more suitable for AI-based MaaS applications.

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