Anomaly Detection for Traffic Management Purposes at Urban Intersections Using Infrastructure-Generated Vehicle-to-X Messages

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Abstract: Reliable detection of problematic system states in traffic management poses a significant challenge. Failures in detection can result in the inability to intervene in a timely manner, while excessive detection may lead to operator fatigue, causing critical information to be ignored amidst an overload of irrelevant messages. Light-controlled intersections represent both safety and efficiency-critical locations within urban traffic networks. Anomalies in these traffic system units can manifest at various levels: technically/physically within the control systems (actuators, sensors, communication technology), at the traffic data level (reliability and completeness of collected traffic data), and in traffic observation (unusual traffic flows, unusual objects). Anomaly detection occurs across these different levels using various methods (technical and algorithmic). Vehicle-to-Everything (V2X) communication provides an additional data source for monitoring the correct and efficient operation of traffic signal systems. This paper presents strategies for leveraging the diverse messages from V2X communication to identify unusual system states across these levels. We demonstrate our approaches at an urban intersection within the Digital Testbed Dresden.

1 INTRODUCTION

Intersections are critical components of urban road networks with regard to efficiency and safety. As conflicts in these areas are a main reason for severe urban accidents (Destatis, 2022) as well as bottlenecks for the overall throughput of a network, effective traffic flow and incident management is a major task at urban intersections.

Traffic monitoring has therefore been studied for decades (Aymerich and Novo, 1992), and a broad range of detectors is available for this task (Klein, 2020).

An emerging additional source is the growing V2X communication with standardized messages allowing all traffic participants, including the infrastructure, to share information about the current traffic situation.

There is a steadily growing number of cities implementing the necessary communication infrastructure at signalized intersections (Auerswald et al., 2019). In Europe, the European C-Roads initiative (C-Roads Germany, 2024) has advanced the standardization and implementation of V2X messages, including cross-border testing. Since 2019, the Digital Testbed Dresden has been part of this initiative, marking the transition of C-ITS to urban test sites. Consequently, C-Roads serves as a foundation for further scientific projects, such as STREAM [1].

On the other hand, the number of vehicles equipped with the necessary communication equipment is rising as well (Yu et al., 2022).

As already stated, urban traffic management including online detection of incidents and anomalies has been studied for decades. To our knowledge, using V2X messages for reliable anomaly detection in productive urban traffic monitoring is, however, an open issue.

In this paper, we will discuss the current state of the art concerning V2X communication as well as anomaly detection in traffic monitoring in Section 2. We will outline a methodology for using standardized

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[1] Project reference: https://www.europa-frdert-sachsen.de/de/projekte/49528

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V2X messages as a basis for anomaly detection in Section 3 and show its application at an urban intersection of the Digital Testbed Dresden in Section 4. The paper is concluded in the final section.

2 STATE OF THE ART

Conventional traffic monitoring relies on various types of traffic flow detectors, such as induction loops, radar, and infrared sensors. These devices are typically embedded in the road surface or positioned alongside the roadway to collect data on vehicle counts, speeds, and classifications. Induction loops, for example, detect the presence of vehicles by measuring changes in inductance caused by the metal mass of vehicles passing over them. While these methods have been effective for many years, they have limitations in terms of coverage, flexibility, and the granularity of data collected.

As traffic management systems evolve, the integration of V2X communication presents significant advantages over conventional methods. V2X communication units can generally be divided into Road-Side Units (RSUs), which are, e.g., installed at (signalized) intersections, and On-Board Units (OBUs), which are mounted in various types of vehicles, like passenger cars, buses or trams. The following are key types of V2X messages currently available (Rondinone and Correa, 2018) and operational in the Testbed Dresden ((Strobl et al., 2019), (Auerswald et al., 2019), (Klöppel-Gersdorf et al., 2021)):

- **Map Extended Message (MAPEM):** This message contains detailed information about the topology of an intersection, including lane configurations, road geometry, and other relevant traffic features.
- **Signal, Phase and Timing Extended Message (SPATEM):** This message provides information on the current signal status of traffic lights at an intersection, informing vehicles of the phase and timing of signals to optimize traffic flow and safety. In addition, SPATEM may also contain prognosis data on future traffic light states, facilitating Green-Light Optimized Speed Advisory (GLOSA).
- **Cooperative Awareness Message (CAM)**: This message conveys the current status of traffic participants, including their position, speed, and direction, enabling vehicles to maintain awareness of their surroundings.
- **Collective Perception Message (CPM):** This message includes information about objects detected by traffic participants and infrastructure, facilitating a shared understanding of the environment and enhancing situational awareness.
- **Decentralized Environmental Notification Message (DENM):** This message includes information about possibly dangerous road situations like traffic jams, broken down vehicles, etc. Such messages directly aid in the detection of anomalies.

V2X technology significantly extends the detection range and facilitates real-time data fusion from diverse sources, including vehicles and infrastructure. This integration allows for a more comprehensive understanding of traffic conditions, ultimately leading to enhanced traffic flow, safety, and efficiency.

An anomaly within any road monitoring system is identified when there is a deviation from the expected state across multiple levels of analysis. Anomaly detection have been established based on conventional detection methods, leveraging metrics such as the Level of Service as defined by (Transportation Research Board, 2000) and (FGSV, 2015). V2X messages however deliver information at a much more detailled level, such as vehicle trajectories. Trajectories have not been reflected in current standards.

In the TrafficIQ project (von der Ruhren et al., 2011), a methodology centered on data quality monitoring has been developed, emphasizing that high data quality is crucial for accurate and reliable anomaly detection.

However, to our knowledge, the application of V2X technology for anomaly detection has been limited, as seen in (Klöppel-Gersdorf et al.,), which focuses on Level of Service (LoS) calculations.

This paper aims to present a comprehensive approach to evaluating urban traffic detection setups, with a particular focus on incorporating V2X messages for anomaly detection.

3 METHODOLOGY FOR DETECTING ANOMALIES BASED ON V2X

The methodology for detecting anomalies in connected and automated driving systems leverages the extensive data provided by V2X communication. High data quality is essential for reliable anomaly detection. Therefore, the initial step toward anomaly detection is establishing a data monitoring framework. Anomalies are defined as deviations from expected data in terms of both quality and content (e.g., traffic events)

3.1 General Approach for Anomaly Detection

The established method of data quality monitors (von der Ruhren et al., 2011) can be applied to V2X communication as follows:

1. **Technical Availability:** Ensuring that detection systems are operational and functioning as specified. Anomalies may arise from technical failures, such as RSU outages or sensor malfunctions. Device monitors track the health of individual components, including video capture systems and detection software.
2. **Data Quality Level:** Ensuring that traffic data streams are available and meet predefined quality criteria. Anomalies in this context indicate a loss of data quality, which can stem from inaccuracies in sensor data or communication disruptions. Monitoring the data streams involves evaluating parameters like sensor data accuracy and the plausibility of CPM messages.
3. **Traffic Event Level:** This research focuses on anomalies in observed traffic situations that deviate from expected patterns. By comparing real-time traffic data with prior knowledge, unexpected traffic situations can be identified. This includes analyzing traffic metrics, such as traffic volumes and vehicle types, as well as finding anomalies in traffic scenes. The authors of (Santhosh et al., 2019) categorized anomalies at traffic event level in detail.

The process of anomaly detection involves several key steps, including anomaly definition, data acquisition, preprocessing, feature extraction, and the application and evaluation of machine learning algorithms. This procedure follows the Cross-Industry Standard for Data Mining (Chapman et al., 2000).

1. **Anomaly Definition:** As stated above, anomalies are defined as deviations from the normal state of traffic monitoring systems, taking into account technical, functional, and qualitative aspects. Although we will discuss this broad spectrum of anomalies in the next subsection, we will focus our measurements and discussions on traffic quality-related anomalies.
2. **Data Acquisition:** The initial step involves collecting V2X messages from smart intersections equipped with RSUs and OBU. These messages include CAM, CPM, MAPEM, DENM, and SPATEM.
3. **Data Preprocessing:** The raw data undergoes preprocessing to ensure quality and consistency. This includes handling missing values, filtering out erroneous data, and synchronizing timestamps from different sources. The goal is to create a clean dataset that accurately reflects real-world conditions.
4. **Feature Extraction:** Relevant features are extracted from the processed data to facilitate anomaly detection. Key features include vehicle speed, trajectory information, lane association, and temporal data.
5. **Machine Learning Algorithms:** To identify and classify anomalies, machine learning algorithms such as Support Vector Machines (SVM) and Random Forest can be employed. These models may be trained on labeled datasets to learn patterns associated with normal and anomalous behavior.

By implementing this comprehensive methodology, the research aims to enhance situational awareness and safety in traffic environments.

3.2 Anomaly Detection Algorithms

Following concrete anomaly detection algorithms have been implemented.

Technical Availability. The detection technology (e.g., RSU, OBU) must be operational and functioning according to specifications. Anomalies include technical failures such as RSU outages or sensor malfunctions.

Additional metrics used for calculating technical availability include:

- Public network latency (> 100ms),
- Availability of internal network connection to RSU (yes/no),
- Availability of internal network connection to cameras (yes/no),
- Network stack is running on RSU (yes/no),
- Video processing is running (yes/no).

Data Quality. V2X data streams must be available and meet predefined quality criteria (e.g., accuracy, completeness). Anomalies are identified when data quality falls below these standards, indicating potential errors in traffic reporting.

Traffic Event Level. The primary focus is on unexpected traffic situations that deviate from the expected patterns. Anomalies can be detected by comparing real-time traffic data against historical patterns or established norms.

In our current setup we defined following undisclosed list of anomalies:

- **Speed Associated Anomalies:** Deviations in vehicle speed from expected norms
  - *Overspeeding Anomaly:* For this work we used 50 km/h as boundary to detect overspeeding at the intersection. This is the official speed limit for that intersection.
  - *Static Object Anomaly:* Speed of an object traversing the intersection is recorded as 0 km/h for an extended amount of time.
- **Lane Associated Anomalies:**
  - *Lane Anomaly:* Unauthorized lane usage by vehicles based on the definitions in the MAPEM for that intersection.
  - *U-turn Anomaly:* Unauthorized u-turn based on the authorized lane changes defined in the MAPEM for that intersection.
- **Traffic Flow Anomalies:** Irregularities in traffic counts that deviate from expected distributions.
  - *Traffic Count Irregualrities:* Traffic volume per direction shows major deviation from hourly normal for a typical similar day.
  - *Traffic Count Proportions:* Percentage of trucks amongst all detected vehicles exceeding historical levels, in the given case exceeding 15%.

While this work focusses on the usage of CPM, an earlier study demonstrated the usage of CAM for LoS monitoring in (Klöppel-Gersdorf et al.,). If LoS exceeds certain predefined values, a LoS anomaly could also be defined.

Further traffic scene specific anomalies could also be defined, such as persons at critic regions of the intersection, larger groups of persons on the road or an abnormal distribution of recognized vehicle types, as well as abnormal forms of trajectories of any object.

4 RESULTS AND DISCUSSION

4.1 Data Collection

The anomaly detection methodology was applied during Rutuja Mohekar's master's thesis (Mohekar, 2024). Within the framework of our SmartTrack intersection, our second smart intersection in the Digital Testbed Dresden (the first one had been presented by (Klöppel-Gersdorf et al., 2021)), we collected available V2X messages during the months June to July 2024, especially CAM, CPM and MAPEM. This urban intersection is located at the junction of Bergstraße, Mommsenstraße, and Haeckelstraße. At

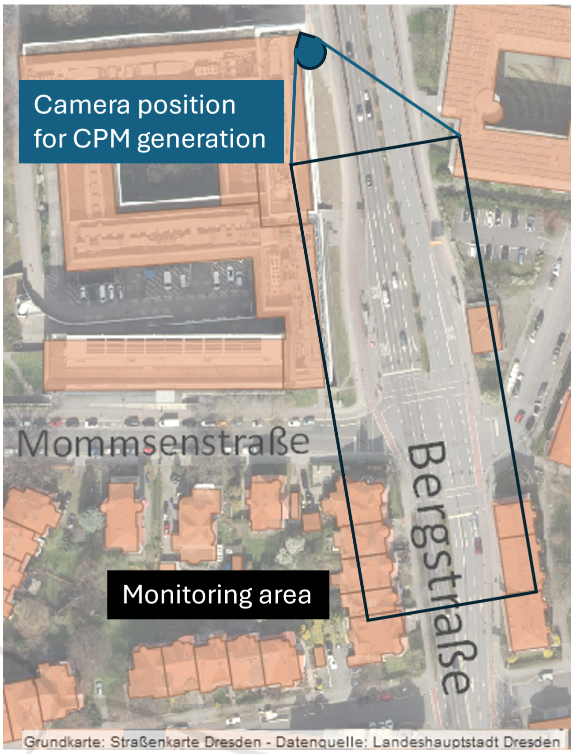


Figure 1: Overview of SmartTrack Intersection (Landeshauptstadt Dresden, 2024).

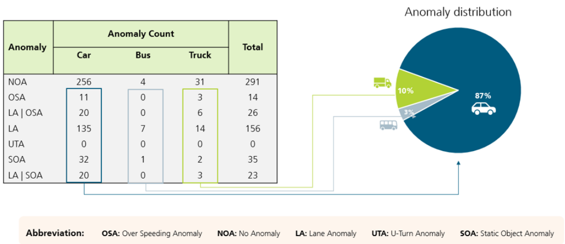
the top of a building belonging to the Technical University Dresden, a Flir Dual Aid Camera has been installed to monitor traffic in the entire conflict area of this intersection. A sketch of the setup is shown in Fig. 1.

4.2 Detected Traffic Anomalies

During the anomaly detection analysis, various traffic flow anomalies were identified in a one-hour assessment. The analysis reveals that the distribution of anomalies strongly correlates with the distribution of vehicles: the more vehicles counted, the more anomalies are detected. An overview of the anomaly distribution can be found in Fig. 2.

Detecting these anomalies is crucial for understanding and improving traffic management at urban intersections.

A large proportion of static objects were left-turning vehicles. These turns regularly led to stopping vehicles in the conflict area of the intersection, as the vehicles had to wait for conflicting traffic streams. These vehicles are currently labeled as "Static Object Anomalies", as they are static objects in the intersection area. In future approaches, we will also use the SPAT message and the stopping duration to classify the type of static object anomaly.



Anomaly	Anomaly Count			Total
	Car	Bus	Truck	
NOA	256	4	31	291
OSA	11	0	3	14
LA | OSA	20	0	6	26
LA	135	7	14	156
UTA	0	0	0	0
SOA	32	1	2	35
LA | SOA	20	0	3	23

Figure 2: Distribution of detected anomalies per anomaly type and vehicle type.

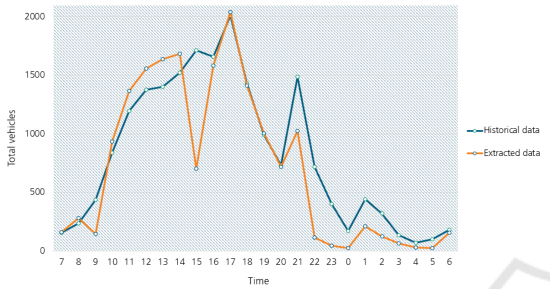


Figure 3: Comparison of inductive loop counts and CPM traffic flow showing traffic flow anomaly.

One example of a detected flow anomaly is depicted in Fig. 3. To determine traffic flow anomalies, we compared the incoming V2X data stream with data from nearby inductive loops. On the day depicted in Fig. 3, we encountered a considerable drop in the number of vehicles around 15:00. For that case, we can show an anomaly in the V2X data stream, which might have occurred due to technical reasons. The inductive loop data show the inductive loop counts for that day as an example of historical data for that site. However, mean values for the current day's category (day of the week, days in conjunction with holidays, seasons, events) could also be used for comparison.

4.3 System Quality Monitoring

The identified anomalies serve not only for detecting traffic issues but also for monitoring system quality. Analyzing the anomalies allows for the identification of potential algorithmic problems that could impair the efficiency of traffic detection.

Key issues identified include:

- **Geolocation Issues:** Difficulties in accurate geolocation can lead to incorrect detections, particularly with speed and lane anomalies.
- **Tracking Issues:** Insufficient tracking of vehicles can result in anomalies not being correctly identified, thereby affecting the reliability of the system.

By continuously monitoring system quality and analyzing anomalies, strategies can be developed to enhance algorithm performance and improve overall traffic safety.

4.4 Key Findings

Following key findings can be stated:

- **Anomaly Detection Success:** The research successfully identified various types of anomalies, including speed-associated anomalies, lane-associated anomalies, and general traffic count anomalies. The application of machine learning algorithms, specifically Support Vector Machines and Random Forest, demonstrated robust frameworks for detecting these anomalies effectively.
- **Traffic Behavior Insights:** The analysis revealed that the majority of detected anomalies were attributed to cars, aligning with the expected distribution of vehicle types. The absence of U-Turn Anomalies indicated compliance with traffic regulations, while the presence of Static Object Anomalies suggested areas for refining detection algorithms to reduce false positives.
- **Temporal Variations:** The study highlighted significant variations in traffic volumes across different times of the day, emphasizing the importance of temporal factors in traffic anomaly detection. Such insights can inform traffic management strategies, including signal timing adjustments during peak hours.

5 CONCLUSION & OUTLOOK

The described findings provide valuable insights for traffic engineers and system operators. By leveraging V2X data, the proposed anomaly detection framework can enhance situational awareness, allowing for more proactive traffic management and safety measures at intersections. The ability to identify and categorize anomalies in real time supports the development of smarter, safer transportation networks. Above, using V2X messages deliveres an appropriate possibility to detect Vulnerable Road Users (VRUs) without additional sensors.

In conclusion, this paper contributes to the advancement of cooperative and automated driving systems by demonstrating the potential of V2X-based anomaly detection. The methodologies developed lay the groundwork for future innovations in smart city infrastructure, with the ultimate goal of enhancing urban traffic safety and efficiency.

While the research achieved its objectives, certain limitations were noted, including the reliance on specific vehicle types equipped with V2X technology and challenges related to data completeness.

With a limited amount of data, the value of using ML approaches is also limited. While we have created an initial proof of concept for this topic, a complete application for larger and more reliable data sets remains a goal for the future.

This approach was tested at one intersection within the Digital Testbed Dresden. Since this testbed consists of further RSU-equipped intersections, we will apply this approach to other intersections with different traffic detection setups. This demonstrates the flexibility of the described approach.

Future work should focus on expanding the dataset to include a broader range of traffic participants, as well as improving algorithms to handle more complex or rare anomaly types. The current work does not use all available V2X information, e.g., the phase information in the SPATEM could be used to detect red-light violations and to specifically label static vehicles which have to wait during left-turns.

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