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On Expressing Automotive Maneuvers with SFC

Bachelor of Science Thesis in Software Engineering and Management

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This research combines existing knowledge on space-filling curves and autonomous driving taxonomies to represent possible maneuvers scenarios and events from real driving data. By doing so, we can possibly reduce testing time and costs, and advance the development of autonomous driving technologies.

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***Abstract*—Conventional methods for testing autonomous driving software often involve dealing with a large number of dimensions, which can complicate the processing and analysis of test datasets. Therefore, there is a pressing need to develop a more efficient approach that is both time and cost-effective. In response to this challenge, our research aims to utilize space-filling curves to effectively represent possible maneuvers within high-dimensional autonomous driving data.**

This study begins by conducting a comprehensive literature survey to explore the existing applications of space-filling curves in the automotive domain. This investigation helps us gain insights into the current state of the field and understand how space-filling curves can be applied to address the complexities of autonomous driving. Additionally, we also review the literature concerning autonomous driving taxonomies to comprehend how existing taxonomies define various autonomous driving maneuvers, events, and scenarios.

***Index Terms*—space-filling curve, software engineering, software testing, taxonomy**

I. Introduction

With the development of Autonomous Driving(AD) technology, software testing has never been more critical in the automotive industry. In fact, the quality and reliability of the software that powers autonomous vehicles can determine whether they are widely adopted or shunned by consumers. Developing robust testing methods to ensure the safety, accuracy, and efficiency of these complex systems is crucial.

Imagine cruising down a highway at 70 miles per hour, enjoying the scenery and the freedom of the open road. Suddenly, a car turns in front of you, causing you to hit the brakes and swerve to avoid a collision. You breathe a sigh of relief and continue on your way, but what if you weren't the one driving that car? What if it was an autonomous vehicle, relying on software to make life-or-death decisions in an instant?

Testing and evaluation of autonomous vehicle systems have become essential components of autonomous driving development, as they are critical to ensuring accurate decision making and improving software quality. They also serve as fundamental building blocks for the advancement of autonomous driving technology. According to [1], autonomous driving testing requires billions of miles of real-world road testing, but virtual environment scenario testing can effectively reduce costs. The biggest challenge, however, is selecting a suitable simulation framework and choosing relevant scenarios for the system under test. This requires more clear and systematic definition and classification standards for testing scenarios, as well as a reevaluation of driving behavior judgment criteria from the perspective of autonomous driving, using vehicle sensor data as the basis for decision-making, to ensure that the software can make safe and accurate judgments. The study by Sippl et al. in[2] demonstrates how scenario-based testing can be used throughout the entire development process of autonomous driving systems.

Fully autonomous driving relies heavily on data input from the vehicle's own sensors[3], which serve as the "eyes" of the vehicle, while the onboard chips act as the "brain". The way in which the data is transmitted, stored, and processed will affect the speed and accuracy of the vehicle's decision-making process. S. Fürst's [4] 2019 study highlighted the importance of updated technology in several aspects of autonomous driving software: sensor technology, high-performance computing, AI and machine learning, and software design paradigms.

A. Problem Domain & Motivation

In this paper, we will present a data model called Space-Filling Curves (SFCs) [5], which is a spatial indexing technique used for data compression and fast search. This relatively new technology highlights the importance of understanding the application and research status of SFCs in the field of autonomous driving. By screening the literature, we aim to identify the domains and scenarios where SFCs have been utilized and studied in the automotive domain.

Given the complexity and diversity of the autonomous driving domain, a systematic approach is needed to describe the different scenarios and events. Currently, various national autonomous driving dataset platforms use different criteria to classify autonomous driving projects, with the aim of better understanding and analyzing different driving situations. Therefore, our research is motivated by conducting a literature survey to learn the relationship between vehicle action judgments and data changes in autonomous driving technology so that we can know what kind of data can define an autonomous driving event, such as criteria for triggering events, criteria for completing events, coordination and balance between time data and speed data, etc. Specifically, we will focus on taxonomies that can describe autonomous driving scenarios and events, and characterize these scenarios and events by interpreting what are the main influential factors.

The following is an example of SFCs in Fig. 1. Which is illustrate how the z-order curve overlays the surface.

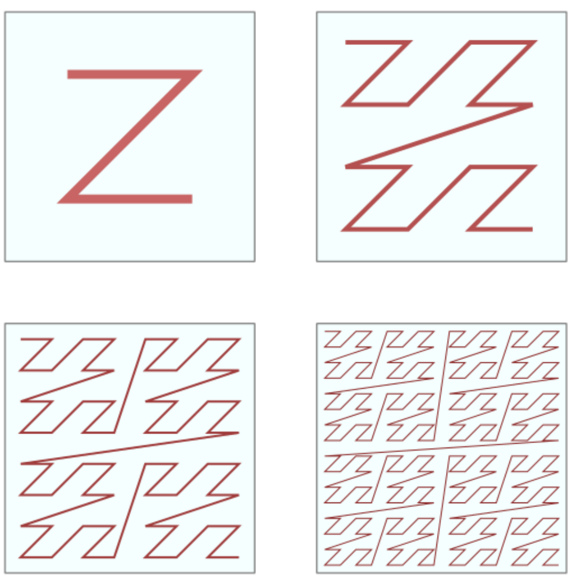


Fig. 1. One example of Space Filling Curve

In AD, testing the autonomous driving software requires large amounts of data and highly detailed annotations to ensure the software can accurately predict and respond in different situations. However, these datasets are often very large, with dimensions and quantities that exceed the computer's processing capacity. By using SFCs technology, we can map high-dimensional data to one-dimensional space, reducing the dimensionality of the test dataset and making it easier to manage and process. This will enable us to more efficiently test autonomous driving software and reduce testing time and costs. Currently, a direct search for "Space Filling Curve" on academic literature platforms yields over 2,600 results. Our approach is to filter the literature to determine the usage of SFC in the field of automotive autonomous driving thus far. We believe that applying SFC technology can enhance the testing efficiency of autonomous driving software and contribute to the development of autonomous driving technology.

SFCs are a math method used to map two-dimensional or three-dimensional spatial data to a one-dimensional curve. In simple terms, it can map a complex spatial structure to a simple linear structure, making it easier to process and analyze spatial data. The special feature of this curve is that it not only preserves the topological relationship of spatial data but also maintains the local and global structure of the data. According to [5], SFC has the prospect of opportunities for use in GPS, computer graphics and other areas.

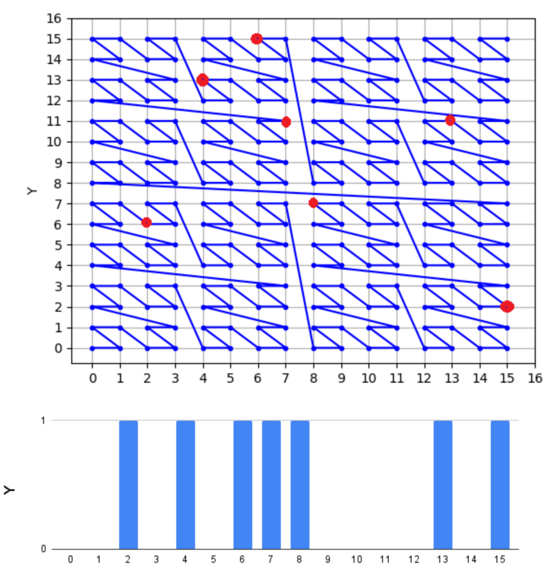


Fig. 2. One example of CSP

Characteristic Stripe Pattern (CSP) (as shown in Fig. 2) is a pattern generated from "z-order curves" in SFCs, The CSP graph is created by marking specific points(those red points in Fig. 2) in this model and then drawing vertical bar(those blue bar in Fig. 2) graphs at the marked points, resulting in multiple bars in the CSP graph. By analyzing CSP, we can study the relationship between driving actions and the one-dimensional data generated by SFC.

B. Motivation & Research Goal

The CSP graph is based on sensor data from the vehicle, which contains information about the vehicle's actions based on data changes, such as an increase in longitudinal acceleration during acceleration, a decrease in speed and a change in latitudinal acceleration during a turn. Therefore, it is appropriate to use a CSP graph that corresponds to the vehicle maneuver data. Before that, it is important to understand how the current taxonomy describes the maneuvers and events, and which symbols or features can represent a maneuver. This is an essential prerequisite for drawing the CSP.

When we talk about taxonomy, it refers to a system of categorization. In autonomous driving, taxonomy is used to describe different types of scenarios, events, objects, etc. For example, various driving scenarios encountered by autonomous vehicles can be classified into different types such as highway driving, city road driving, parking, etc. These different types of scenarios can be further divided into sub-types to more accurately describe the behavior, decision-making, and operation of autonomous vehicles in specific scenarios. These taxonomies can help autonomous vehicles better understand their environment and perform corresponding operational behavior. For our research, taxonomy will serve as a reference standard for vehicle behavior data, enabling us to have a more rigorous definition of vehicle behavior and vehicle kinematics.

We will use literature survey methods to search for existing technologies and applications of SFCs in the field of autonomous driving. The purpose of doing so is to avoid duplication of projects already completed by others and to see if there are any other studies that are highly similar to our research since there may be other programs in the autonomous driving system that calls on data recognition of vehicle behavior using SFCs models.

C. Research Questions

Based on our research motivation and goal above we propose these Research Questions:

RQ 1. To what extent are SFCs used for automotive applications?

RQ 2. What taxonomies exist to describe scenarios and events?

RQ 3. What aspects of existing taxonomies for scenario and event description could be supported by characteristic stripe patterns (CSPs) on SFCs?

The purpose of RQ1 is to search for similar or redundant studies in past research. RQ2 aims to collect the autonomous driving data required for the study. RQ3 involves what kinematic parameters/indicators from existing literature/taxonomies can support the plotting of CSP.

D. Contributions

In this study, we conduct a comprehensive survey and analysis of literature pertaining to taxonomy-related topics. Our approach relies on extracting and utilizing kinematic properties and geometric properties derived from the literature to effectively express these maneuvers.

II. Related Work

Based on the survey on the current study, we find the following study was related to this field:

The paper [6] addresses the challenges associated with evaluating the performance, safety, comfort, and efficiency of automated vehicles during their development. Traditional scenario-based testing of these vehicles required manual identification of scenarios from extensive datasets, which limited flexibility and posed difficulties in defining valuable scenarios. To overcome these limitations, the paper proposes a two-step method for mining scenarios from real-world data of individual vehicles.

In the first step, the method automatically assigns tags to the data, providing explanations for various activities performed by different actors, such as lane following or lane changing. This tagging process enables the identification and categorization of the behavior exhibited by the ego vehicle, the behavior and state of other vehicles, and the characteristics of the static environment. The second step involves mining scenarios by searching for specific combinations of tags, allowing for a more targeted analysis of relevant situations. To facilitate the data tagging process, the paper presents an algorithm that detects and labels longitudinal and lateral activities of vehicles using sensor data, with a particular focus on events such as acceleration and lane changes. This algorithm is designed to handle missing data and account for short cruising activities, ensuring robust and accurate labeling of the dataset.

The key finding of this paper is that employing this flexible and scalable method for mining scenarios from real-world data enables effective scenario-based testing of automated vehicles. This approach facilitates the extraction of meaningful insights and learnings regarding their performance and behavior, enhancing the overall understanding and optimization of automated vehicle operations and safety.

In another study [7], researchers constructed scenario categories using naturalistic driving data and detailed accident databases. These scenarios were categorized based on their environment, ego-vehicle objectives, and actor type. A tagging system was developed to support scenario selection. Parameters were quantified to generate test cases and evaluate key performance indicators for safe automated vehicle operation.

The third related study [8] presents an innovative approach called Z-order Curve-based Event Retrieval Approach (ZEBRA) that aims to enhance the efficiency of processing large-scale automotive data sets.

The key finding of this study is the combination of SFC-based dimensionality reduction with the temporal properties derived from the Operational Design Domain (ODD) of the data space. This combination enables the ZEBRA approach to achieve computationally efficient event detection and retrieval, particularly demonstrated in the context of maneuver detection within an automotive data set. The results demonstrate that the proposed approach significantly reduces processing time when compared to traditional methods of event detection. Furthermore, the ZEBRA approach offers the advantage of providing analytical explainability for the detected events, enhancing the interpretability and understanding of the processed data.

Although the aforementioned research makes a valuable contribution to scenario mining and scenario categorizing, it acknowledges a limitation in precisely identifying the primary factors that influence driving maneuvers. To overcome this limitation, our research focuses on developing a taxonomy of the key aspects that exert the most significant influence on driving maneuvers. Our aim is to identify and categorize these influential factors, providing guidance and references for those involved in the development of test cases for autonomous driving. We expect that this taxonomy will enhance the understanding of the underlying factors that shape driving maneuvers, thereby facilitating the design and evaluation of autonomous driving systems.

III. Methodology

We will use the Literature Survey as our research methodology.

The literature search engine used in this paper is google scholar, through which we can search the literature in several academic databases, among which the main sources of results are from (PubMed, IEEE Xplore, ACM Digital Library, ScienceDirect, etc.). We will identify several key literature as our golden literature through a literature survey, and analyze this golden literature in the result section.

Screening criteria for RQ1 and RQ2: We prioritize finding studies in recent years and screen them as the latest literature after 2020. Secondly, we prioritized the literature that was recommended by google scholar first, and the literature that were cited a lot.

By searching for keywords (space filling curve, auto driving, automotive) we get about 17,000 results, which is too many for us, we will keep the initial keywords and add more keywords to narrow the scope.

To address RQ1, we will have 2 search queries:

Search query 1:

We selected the initial keywords:

- ”space filling curve”
- ”SFCs”
- ”auto driving”
- ”autonomy”
- ”automotive”

(space filling curve, SFCs, auto driving, autonomy, automotive) to search the literature on the google scholar academic platform, and after filtering through the year 2020, 312 results were obtained.

The terms ”point cloud” and ”LiDAR point cloud” appear four times in the top five results. Four of these articles were formally cited.

We read the first four articles and used the first two search results as the gold literature, from Xi Xiang 2022 [9], ”Extraction of local structure information of point clouds through space-filling curve for semantic segmentation”, from the academic platform ScienceDirect, which was cited 2 times. Another article from J.Castagno 2020 [10] Polylidar3D-Fast Polygon Extraction from 3D Data”, an article from the academic platform MDPI, cited 8 times.

search query 2:

We have removed the keyword (SFCs) from the original keywords:

- ”space filling curve”
- ”auto driving”
- ”automotive”

(space filling curve, auto driving, automotive), which will lead us to search for other proper names with the same abbreviation (e.g. Service Function Chaining, side-force coefficient). The new keyword

- ”algorithm”

(algorithm) was added and after filtering 2020, 16,900 search results were obtained. Among the first ten suggested papers, five articles mention path/motion/trajectory planning methods for vehicles in their abstracts. and control method for autonomous vehicles based on the RRT algorithm”[11] as Gold. Cited 28 times, with the most citations in the top ten results.

In addition, one of these ten articles from IEEE mentions another approach to the application of SFCs technology, from Songzhan Lv, 2021: ”PLVA: Privacy-Preserving and Lightweight V2I Authentication Protocol”[12]. This paper applies SFCs technology to the encryption of private information in vehicles, with a tendency toward cryptographic applications.

For RQ2, we searched for taxonomies from academic platforms and, through our filtering, selected those taxonomic literature that were most helpful to our study as our gold literature.

Search query 1:

The initial keywords:

- ”Taxonomy”
- ”Scenario Classification”
- ”auto driving”
- ”automotive”

(Taxonomy, Scenario Classification, auto driving, automotive) were searched on the Google Scholar academic platform and, after filtering to the year 2020, approximately 17,100 results were found.

Adding further keywords:

- ”Literature review”
- ”scenarios”
- ”events”

(Literature review, scenarios, events), 17,100 results were also found. This number of results was not narrowed down in our further additions, with 15,100 results after advancing the year to 2021 and around 8,700 results after advancing the year to 2022, but with a lower number of citations. So we kept the scope beyond 2020 and started browsing the literature in the results of the seven keyword searches above.

Here we go through the first five pieces of literature and find two pieces of literature recommended from the academic platform. The first recommended literature, D. Nalic 2020[1](Taxonomy Gold Literature 1), from the academic platform Research Gate, is cited 43 times and describes which classifications can be used to describe scenes. The second recommendation is S. Riedmaier 2020 [13](Taxonomy Gold Literature 2), which had 207 citations and was hit for keywords such as literature review, scene classification, event classification. These two literature were used as the gold literature for learning taxonomies, and we will summarise the parts of them that are useful for our research to answer our research questions.

Search query 2: Reading through S. Riedmaier’s literature[13], we noticed that they mention the concepts of Object and Event Detection and Response (OEDR) and Operational Design Domain (ODD) in the section on Safety Assessment and Verification Scenarios, where it is introduced that OEDR can check if the vehicle is able to detect objects and events correctly, and we thought this would be useful to describe an autonomous driving event and investigate it further. So we snowballed through the literature to find the two papers that were cited in the OEDR position, namely in their literature (the citation number[8][9]), the first of which is no longer a valid link, and the second cited literature is ”A Framework for Automated Driving System Testable Cases and Scenarios, 2018” [14](Taxonomy Gold Literature 3), from the U.S. Department of Transportation, which will serve as the third gold literature in the taxonomy.

To address RQ 3, we will employ a literature survey method, building upon the findings from RQ1 and RQ2. Utilizing the aforementioned platform(Google Scholar, IEEE Xplore, and ACM digital library), we will conduct targeted searches to gather relevant studies on specific driving maneuvers. And also combining the taxonomy concept from the result of RQ2.

Selection Criteria	
Relevance to Maneuver	Select studies that specifically focus on the intended maneuver. And the literature title should include the key words
Publication Date	Consider studies published from 2000 to 2023 to ensure relevance to current research trends.
Context	The research sample represents diverse driving conditions in Europe and driver populations to capture a wide range of intended maneuvers. This study should mention what specific feature of this intended maneuver they will focus on.

Fig. 3. Selection Criteria

First, we will focus on specific scenarios by using keywords related to vehicle maneuvers to filter the literature. This search will allow us to identify studies that provide insights into the behavior and characteristics of vehicle maneuvers. To narrow down the search results, we will combine these keywords with other related words. Additionally, we will refer to the search criteria table Fig. 3 to guide our literature search. Here are the combination keywords we will use:

Keywords for Roundabout:

- ”Roundabout”
- ”Vehicle Roundabout”
- ”Autonomous Driving Roundabout”
- ”Kinematic Roundabout”

Keywords for Emergency Brake:

- ”Emergency Brake/Emergency Braking”
- ”Vehicle Emergency Brake/Emergency Braking”
- ”Autonomous Driving Emergency Brake/ Emergency Braking”
- ”Kinematic Emergency Brake/Emergency Braking”

Keywords for Lane change:

- ”Lane change/Lane changing”
- ”Vehicle Lane change/Lane changing”
- ”Autonomous Driving Lane change/Lane changing”
- ”Kinematic Lane change/Lane changing”

Throughout this process, we will gather important influential factors from the identified studies and record them in a table. The table will consist of rows representing the different maneuvers identified in the scientific papers. The columns will list various signals or influential factors, and we will mark the corresponding cells with dots to indicate which signals are suggested for identification.

IV. Results

A. *RQ1 results*

Based on the ”Search queries” from the methodology, we sorted out the following literature and questions to understand the current situation of SFCs in automotive.

- What is a point cloud?
  As introduced in the Lokugam 2022 study [15], LiDAR (Light Detection and Ranging) is a technology that uses light, usually a laser, to detect and measure the distance of objects. It is widely used in modern smart devices and autonomous driving technology, among others.LiDAR provides geo-referenced information with a clear geo-reference by generating a collection of 3D point data. These collections of point data are called point clouds (PCs).

- What is the relationship between point clouds and SFCs?
  Point clouds are 3D object representations obtained by 3D sensors and scanners, and their disordered structure makes them a hot problem in the field of computer vision, according to Xi Xiang’s research [9], which refers to point clouds. Traditional convolutional neural networks cannot directly process point cloud data, so a method of rearranging point clouds to form ordered point clouds using Morton SFC is proposed to improve the feature extraction and semantic segmentation performance of point clouds.
  Their product is presented in the J Castagno 2020 article[10]: Polylidar3D, a non-convex polygon extraction algorithm that simply takes point cloud data as input, determines the presence of obstacles based on the spatial structure of the data and feeds a triangular mesh map as the result. A new method for constructing and using a Gaussian accumulator to identify the principal plane normals in a scene is presented in the article, calling this method the Fast Gaussian Accumulator (FastGA), one of the principles of which is the application of Hilbert curves with space-filling curves.

- Application of point clouds:
  J. Castagno [10] demonstrated the versatility and speed of Polylidar3D with real datasets, including aerial LiDAR point clouds for roof mapping, autopilot LiDAR point clouds for roadway inspection and RGBD cameras for interior floor/wall inspection.
  Xi Xiang’s experimental [9] results show that the two proposed feature extraction modules can effectively extract geometric information from point clouds with strong semantic recognition capabilities. His experimental tests used AI data and autonomous driving data from Semantic 3D and Semantic KITTI datasets, and the proposed models achieved an average concatenated intersection (mIoU) of 70.6% and 47.8%, respectively. In his paper, he also describes that point cloud processing has become an active research area in the field of computer vision and that their research project ”Point Cloud Semantic Segmentation” can be used for a variety of applications: basic mapping, smart city construction and autonomous navigation.

B. *RQ2 Results - Golden Literature*

According to the search results, we collected the following taxonomies:

Gold Literature 1[1]:

- Firstly, the first scenario taxonomy mentioned in that literature is divided into a functional scenario, a logical scenario, and a concrete scenario[16]. The

functional scenario can be described in language, the logical scenario uses a matrix of parameters and procedures, while the concrete scenario simply uses parameter values.
- Other cited taxonomies are also mentioned in the literature, Ro-darius [17] classifies driving scenarios and traffic scenarios, and Elrofai et al[18] introduce urban scenarios according.
- In the cited literature [19], Mahmud's study of safety indicators refers to the TTC (Time To Collision) classification method, which is a time-based classification method that measures the minimum time it takes for two vehicles (or obstacles) to reach the point of collision at the current speed relative to each other. When the TTC value is less than a certain threshold, it is considered a potentially dangerous event WTTC (Worst TTC).

TTC (Time To Collision) taxonomy, we searched for this taxonomy term (Time To Collision, taxonomy) on a separate academic platform and filtered it for 2020 onwards, yielding around 1,8000 results, which shows that TTC is heavily used in the field of vehicle safety performance assessment and we also use this taxonomy as a reference for lane change events and emergency braking events, collecting values for the parameters of such driving events, i.e. time, speed, longitudinal acceleration and lateral acceleration. The TTC taxonomy can measure the occurrence and severity of a vehicle event based on these values and is considered to be very suitable for describing events.

Gold Literature 2[13]:

The literature presents a framework for scenario classification and the steps to perform scenario identification/scenario classification, including framework development, data source identification and acquisition, validation of the scenario classification algorithm using an existing database, selection of specific scenarios from the scenario database, and application of the selected scenarios to the testing or evaluation of automated driving systems.

The definition in [20] is also mentioned in that literature for three different categories of scenarios. These are the so-called functional, logical, and specific scenarios. For logical and concrete scenarios, all parameters describing the scenario are necessary. Therefore a five-layer model is quoted and used in the literature to construct the parameters [21]. The five layers are as follows:

- Layer 1:Road-level
- Layer 2:Traffic infrastructure
- Layer 3:Temporary manipulation of Assisted L1 and Partial automated driving L2
- Layer 4:Objects
- Layer 5:Environment

The literature proposes its own taxonomy of scenarios based on this model, which for our study is sufficient to describe a complete scenario.

Gold Literature 3[14]:

On page 67 of this literature, a detailed description is provided of the OEDR baseline, which serves to identify important objects and events that may be encountered in a given driving environment and to provide relevant object and event information for the selected automated driving system function. The literature shows in diagrams how some events can be classified in areas around the autonomous driving system, for example in front, to the side, and to the rear. These objects can be obstacles or animals, and the literature also provides several tables to list objects and events in the usual driving environment. To briefly summarise, for object detection, event recognition, and event determination in OEDR the following four types of data are required:

- Object data: Used to detect and identify relevant objects in the environment, including permanent and temporary obstacles.
- Environment data: Describes possible obstacles on the road and the operational parameters of other road users, such as the braking capacity of leading and following vehicles and whether other vehicles are behaving abnormally.
- Driver data: Covers cooperative drivers, uncooperative drivers, malicious drivers, and drivers who are distrustful of the automated driving system.
- Road user data: Covers special purpose vehicles, temporary structures, street food and drink, street festivals, children's rides, and other road users.

C. RQ2 Results - Super Taxonomy

1) Super Taxonomy - Design Process: According to OEDR taxonomy, which is a taxonomy to derive the current vehicle events based on the scenario environment, so we designed the architecture to do the current scenario first to get a result and then use this feature of OEDR to make an event judgement. So scenario recognition is done first, then event prediction, and finally event recognition.

Therefore, the order of the taxonomies is:

1. Scenario Taxonomy: Five Layers
2. Scenario-Event Taxonomy: OEDR
3. Event Taxonomy: TTC

We also refer to the scenario taxonomies (Descriptive Scenarios, Logical Scenarios, Concrete Scenarios) to better describe what type of data or text is used to describe the scenarios in each step. Specific scenarios are described in terms of parameters, whereas logical and descriptive scenarios are described in terms of text and functionality, and will be used in our framework as descriptions of the scenarios and events that are eventually recognised.

2) Super Taxonomy - Introducing Taxonomy Modules: The following are the three primary Golden Literature taxonomies that we used primarily in our super taxonomy to describe scenarios and events. Leveraging the strengths and characteristics of the aforementioned taxonomies, we incorporated them into the design of the super taxonomy.

- Super Taxonomy- Five-Layer Parametric Model of Scenarios
  Necessary scenario data: road traffic infrastructure, physical geometric properties of objects and environment, time of day.
  Scenario description: logical and specific scenarios, dependent parameters.
  Applicable scenario types: all.
- Super Taxonomy - OEDR and ODD
  Applicable scenarios: static/dynamic scenarios related to other vehicles or obstacles around vehicles. The taxonomy applies to all possible events in a specific scenario.
- Super Taxonomy - TTC (Time Based Collision)
  Necessary vehicle kinematic data: time, speed, lateral longitudinal acceleration
  Suitable for describing event types: vehicle collision detection, emergency braking. Hazard prediction.

3) Super Taxonomy - Detailed Description: Here is the complete top-down flowchart of the super taxonomy (Fig. 4)

Stage 1. Scenario Recognition

- Step 1. Read camera radar sensor data, measure road parameters and collect necessary road geometric attribute dataset.
- Step 2. Read vehicle speed, acceleration, time parameter values and collect vehicle kinematics dataset
- Step 3. Determine the current scenario based on the road data and validate it with the vehicular kinematics dataset.

Stage 2. Event Prediction

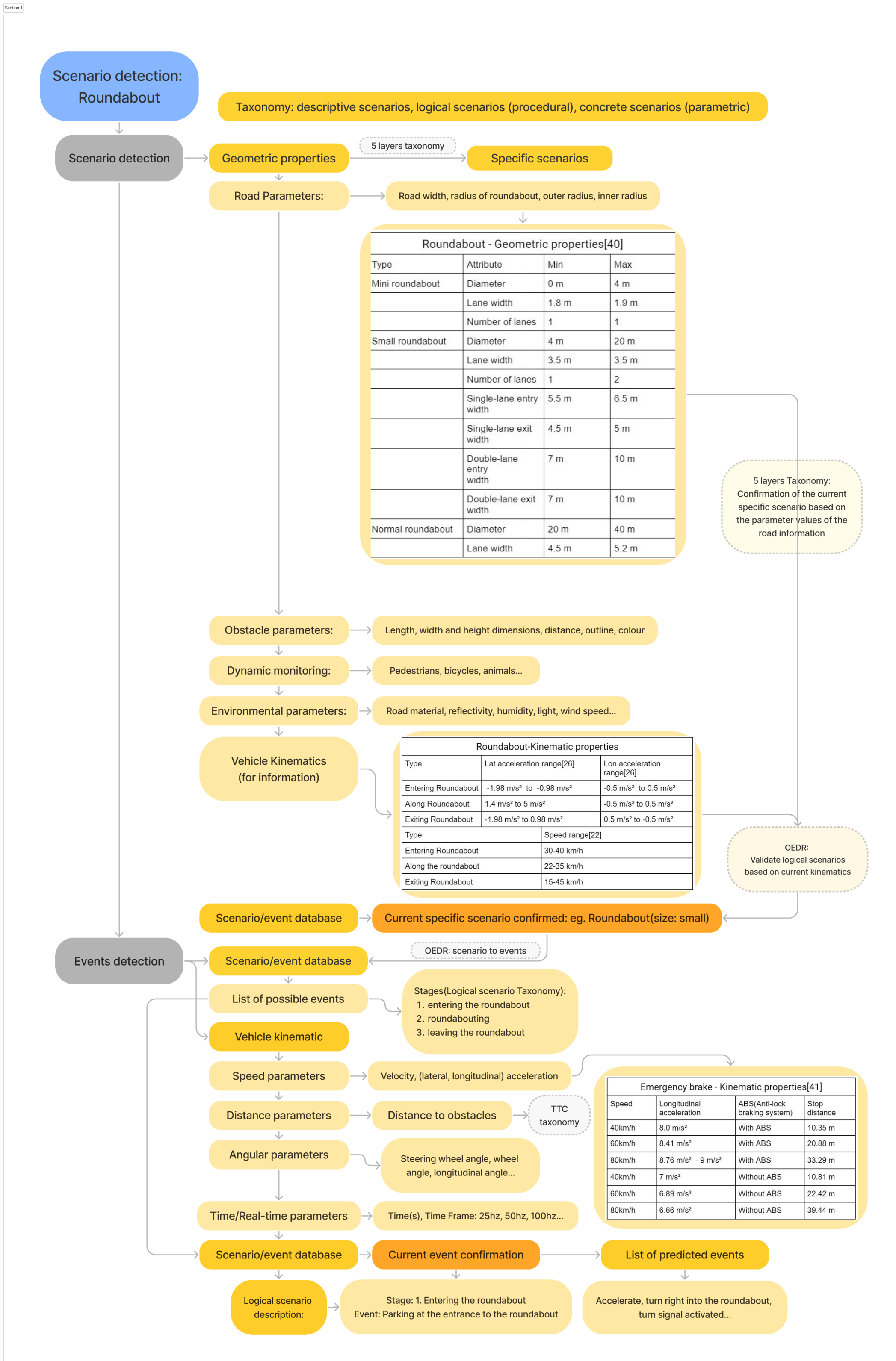
- Step 4. Predict the next possible events based on the identified current scenario
- Step 5. Prepare a list of events predicted to occur and wait in the buffer to be called

Stage 3. Event Recognition

- Step 6. Read the vehicle kinematic parameter values to determine the current vehicle maneuver event.
- Step 7. Match with the predicted event list to identify the current event
- Step 8. Describe the current vehicle scenario/event in a logical scenario format

4) Super Taxonomy - Overview:

- In the following page(Page 9)



Roundabout - Geometric properties[40]

Type	Attribute	Min	Max
Mini roundabout	Diameter	0 m	4 m
	Lane width	1.8 m	1.9 m
	Number of lanes	1	1
Small roundabout	Diameter	4 m	20 m
	Lane width	3.5 m	3.5 m
	Number of lanes	1	2
	Single-lane entry width	5.5 m	6.5 m
	Single-lane exit width	4.5 m	5 m
	Double-lane entry width	7 m	10 m
	Double-lane exit width	7 m	10 m
Normal roundabout	Diameter	20 m	40 m
	Lane width	4.5 m	5.2 m

Roundabout-Kinematic properties

Type	Lat acceleration range[26]	Lon acceleration range[26]
Entering Roundabout	-1.98 m/s² to -0.98 m/s²	-0.5 m/s² to 0.5 m/s²
Along Roundabout	1.4 m/s² to 5 m/s²	-0.5 m/s² to 0.5 m/s²
Exiting Roundabout	-1.98 m/s² to 0.98 m/s²	0.5 m/s² to -0.5 m/s²

Type	Speed range[22]
Entering Roundabout	30-40 km/h
Along the roundabout	22-35 km/h
Exiting Roundabout	15-45 km/h

Emergency brake - Kinematic properties[41]

Speed	Longitudinal acceleration	ABS(Anti-lock braking system)	Stop distance
40km/h	8.0 m/s²	With ABS	10.35 m
60km/h	8.41 m/s²	With ABS	20.88 m
80km/h	8.76 m/s² - 9 m/s²	With ABS	33.29 m
40km/h	7 m/s²	Without ABS	10.81 m
60km/h	6.89 m/s²	Without ABS	22.42 m
80km/h	6.66 m/s²	Without ABS	39.44 m

Fig. 4. Super taxonomy: Integrate taxonomies from RQ2

D. RQ3 Results

As we described in the methodology, the following tables illustrate the search results.

Searching results of Roundabout:

	Roundabout	Vehicle Roundabout	Autonomous Driving Roundabout	Kinematic Roundabout
Google Schoolar	2,380	67	5	2
IEEE Xplore	128	35	2	0
ACM Digital Library	7	0	0	0

Fig. 5. Searching results of Roundabout

Searching results of Emergency Brake:

	Emergency Brake/ Emergency Braking	Vehicle Emergency Brake/Emergency Braking	Autonomous Driving Emergency Brake/Emergency Braking	Kinematic Emergency Brake/ Emergency Braking
Google Schoolar	213 / 924	17 / 99	0 / 10	0 / 5
IEEE Xplore	129	28	2	0
ACM Digital Library	4	0	1	0

Fig. 6. Searching results of Emergency Brake

Searching results of Lane change:

	Lane change/ Lane changing	Vehicle Lane change/ Lane changing	Autonomous Driving Lane change/Lane changing	Kinematic Lane change/Lane changing
Google Schoolar	1920 / 1520	325 / 259	38 / 14	7 / 1
IEEE Xplore	714	237	28	1
ACM Digital Library	27	8	0	0

Fig. 7. Searching results of Lane change

After applying our selection criteria, the literature related to specific roundabout features is presented in Table 8.

Title	Search key words	Cition number	Publish year
Analysis of Kinematic Parameters and Driver Behavior at Turbo Roundabouts," Journal of Transportation Engineering Part A: Systems [22]	Kinematic Roundabout	27	2018
Autonomous Driving in Roundabout Maneuvers Using Reinforcement Learning with Q-Learning[23]	Autonomous Driving Roundabout	44	2019
Autonomous driving manoeuvres in urban road traffic environment: a study on roundabouts[24]	Autonomous Driving Roundabout	47	2011
Investigation of models for relating roundabout safety to predicted speed[25]	Roundabout	57	2013
Lateral acceleration of passenger vehicle in roundabouts in term of cargo securing[26]	Autonomous Driving Roundabout	0	2022
Machine Learning Techniques for Undertaking Roundabouts in Autonomous Driving.[27]	Autotonomous Driving Roundabout	8	2019
Modeling driver behavior at roundabouts: Results from a field study[28]	Roundabout	44	2017

Fig. 8. Filtered Literature Mentioning Specific Roundabout Features with Search keywords, Citation Number, and Published Year

The selected papers include a study [22] on vehicle kinematic parameters such as speed and acceleration, another paper [23] analyzing various kinematic parameters including GPS position, velocity vector components, lane deviation, and speed prediction models adjusted to different roundabout segments. Additionally, there is a study [24] focusing on lateral control for autonomous vehicles using distance to the curve and angular error as kinematic parameters, and another paper [25] examining average speeds, speed differentials, and speed prediction models for roundabouts. Furthermore, a study [26] investigates vehicle dynamics during the roundabout passage, considering lateral acceleration, speed, and acceleration, as well as the importance of cargo securing. Lastly, there are studies [27], [28] that analyze the kinematic parameters of vehicle speed, steering angle, and steering angle velocity in relation to driving behavior at roundabouts.

The filtered literature pertaining to specific emergency brake features is displayed in Table 9. The papers include

Title	Search keywords	Cition number	Publish year
Analysis of emergency braking of a vehicle[29]	Emergency braking	112	2007
Situation assessment of an autonomous emergency brake for arbitrary vehicle-to-vehicle collision scenarios[30]	Vehicle Emergency Brake	252	2009
Volunteer occupant kinematics during driver initiated and autonomous braking when driving in real traffic environments[31]	Kinematic Emergency Brake	51	2011
Autonomous emergency braking test results [32]	Autonomous Driving Emergency Brake	69	2013
Driver braking behavior analysis to improve autonomous emergency braking systems in typical Chinese vehicle-bicycle conflicts[33]	Autonomous Driving Emergency Brake	56	2017
An automobile detection algorithm development for automated emergency braking system[34]	Emergency Braking	11	2014

Fig. 9. Filtered Literature Mentioning Specific Emergency Brake Features with Search keywords, Citation Number, and Published Year

a study [29] examining braking parameters such as the distribution coefficient of braking forces, maximum braking acceleration, braking distance, and settled deceleration. Another study [30] investigates energy reduction and collision prediction algorithms for vehicle-to-vehicle collision scenarios, considering kinematic parameters such as speed, acceleration, turn radius, and lateral offset. The influence of object orientation and classification on the efficiency of emergency brake systems is also explored. Additionally, a study [31] analyzes the forward motion of driver and front-seat passenger volunteers in response to low-g longitudinal deceleration, considering factors such as gender, size, braking levels, and seat belt properties. Another study [32] evaluates the kinematics of Autonomous Emergency Braking (AEB) systems in different test scenarios, assessing the performance and variations in implementation and effectiveness among vehicles equipped with AEB systems. Furthermore, a study [33] investigates drivers' pre-decelerating and emergency braking behavior in V-B conflicts using speed and brake features. Lastly, a study [34] focuses on the detection of speed, acceleration, and trajectory of detected vehicles.

The results of the literature review related to specific lane change features are presented in Table 10. The studies include research [35] on kinematic parameters of Connected and Autonomous Vehicles (CAVs) for lane-changing decisions, considering factors such as position, speed, acceleration, mass, mechanical efficiency, tire radius, integrated aerodynamic drag coefficient, and coefficient of rolling resistance. The aim is to develop a dynamic lane-changing model for CAVs that ensures safe and comfortable maneuvers. Another paper [36] examines the kinematic characteristics of lane change maneuvers, comparing manual driver-performed lane changes with Tesla's Auto Lane Change feature in terms of speed, acceleration, braking events, and duration. Additionally, a paper [37] focuses on the kinematic and dynamic analysis of lateral acceleration during lane-changing maneuvers. A study [38] investigates kinematic parameters such as positions, speeds, accelerations/decelerations, space gaps, and relative speeds of the subject vehicle and surrounding vehicles in the context of lane-changing models. Lastly, a study [39] examines the kinematic parameter of acceleration specifically during the lane-change maneuver.

Title	Search keywords	Cition number	Publish year
A dynamic cooperative lane-changing model for connected and autonomous vehicles with possible accelerations of a preceding vehicle[35]	Autonomous Driving Lane changing	20	2021
Characterizing the use of Tesla's Auto Lane Change Feature in Driver-Initiated Maneuvers[36]	Lane Change	1	2022
Research on Lateral Acceleration of Lane Changing[37]	Lane Changing	4	2019
Lane changing models: a critical review[38]	Lane Changing	170	2010
Kinematic Design for Platoon-Lane-Change Maneuvers[39]	Kinematic Lane change	56	2008

Fig. 10. Filtered Literature Mentioning Specific Lane Change Features with Search keywords, Citation Number, and Published Year

V. Analysis & Discussion

RQ1:

When answering RQ1 using the literature survey method, it is recommended to go for adding keywords to narrow down the literature results based on the strengths and features of SFC, just as we add keywords (algorithms) to find some potential research.

Space-filling curves effectively help to analyze spatial data models. In the field of autonomous driving, point clouds are one of the commonly used spatial data models, which have become popular in recent years with artificial intelligence and autonomous driving, and a large number of articles can be searched based on the term point cloud. According to our results, point clouds are one of the most appropriate answers we found, reflecting the advantages of SFCs in terms of fast data processing.

One of them, Stefano Feraco's vehicle trajectory optimization algorithm, also reflects the fact that space-filling curves can preserve localization between data, and that points that are close in one dimension are also close in the N dimension, but there is no guarantee that the reverse is also true.

Discussion: Based on the results, the application of the SFCs technique can be further explored and discovered based on the application of point clouds, and based on its data indexing advantages, it can demonstrate its advantages and value in projects with large amounts of data and high computational volumes.

RQ2:

According to the golden taxonomy 1[1], we can understand three levels of scene description, through linguistic description, structured, procedural, and in the most detailed way using parameter values, i.e. data.

The scenario taxonomies of urban scenarios and other driving scenarios is necessary and our current research is limited to urban scenarios, with more other driving scenarios to be considered in the future.

TTC (Time To Collision) taxonomy, TTC predicts the incidence and severity of vehicular events based on speed-time values and is considered well suited to describing events.

According to the taxonomy gold literature 2[13], with reference to the five-layer parametric model, we need to provide at least the lowest layer of road geometry data to describe a particular scenario. In the Fig. 11 blow, Shows all the five layers, and we only applied the L1 layer in our super taxonomy at the moment.

According to the taxonomy Golden Literature 3[14]. The taxonomy tends to use a very large framework to summarise all the events that can occur on a vehicle's road.

Discuss these answering taxonomies for describing scenarios/events:

- TTC (Time To Collision)

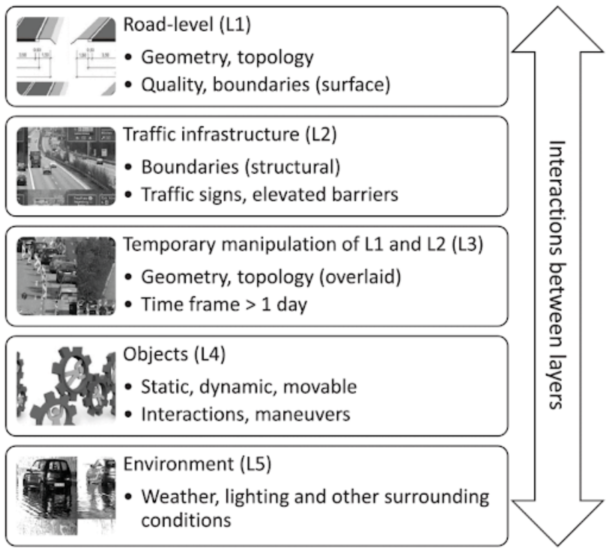


Fig. 11. Five-layer parametric model and interactions between layers[21]

Necessary vehicle kinematic data: time, velocity, acceleration. Suitable for describing event types: vehicle collision detection, emergency braking, hazard anticipation.

- OEDR & ODD
  Necessary scene data: object obstacles, environmental data, driver data, geometric properties of other vehicle occupants. Scenarios suitable for describing events: static/dynamic scenarios with other vehicles or obstacles around the vehicle. The taxonomy is suitable for summarising all events in a scene, or in which scenes a particular event may occur.
- Five-layer parametric model for scenarios
  Necessary scene data: roads, traffic infrastructure, objects, and physical geometric properties of the environment, time. Much like the data required for OEDR, but the model is a parametric model based on a logical scenario and a specific scenario. Suitable for describing the type of scenario: all.

RQ3:

Utilizing the kinematic information extracted from the literature as presented above and combine with the taxonomy concept from RQ2, an indicator table has been formulated. Illustrated in Table Fig. 12, this table delineates the significant indicators for their corresponding maneuvers. These indicators serve as valuable references when interpreting the CSP plot and deciding which dimensions should be incorporated.

	Speed	Longitudinal Acceleration	Latitudinal Accelerati on	Steering Wheel Angle	GPS position
Roundabout	•		•	•	•
Emergency brake	•	•			
Lane Change	•		•		•

Fig. 12. Maneuver Indicator

A. Limitations of this study

For studies based on SFCs that do not mention autonomous driving, and for which the future applications in the field of autonomous driving are not discussed in the article, it is difficult for us to determine the potential applicability of these studies in the future, which may result in missing key literature.

We also need to identify which studies are specifically related to autonomous driving among the relevant research. It is challenging to determine whether a particular functionality is completely unrelated to autonomous driving. Therefore, in the results of answering RQ1, we have listed some literature that does not explicitly mention autonomous driving but we believe has sufficient justifications for inclusion.

Some of the studies mentioned in the literature are overly complex and difficult for us to comprehend with our current knowledge. We lack expertise in automotive engineering and advanced data algorithm knowledge, which may have led to the omission of some highly valuable and renowned literature that requires a higher level of domain expertise to fully comprehend.

Our literature collection process was limited to various academic platforms, including Google Scholar, IEEE Xplore, ACM Digital Library, ScienceDirect, and PubMed. Our understanding of research from non-open platforms is limited due to restricted access.

B. Threats to Validity

1) Internal Threats: Regarding the bias in the search process, we have provided a detailed description of the sources and search methods used in the article, explaining the rationale behind my literature review approach. However, it is possible to miss some relevant literature due to language and geographical differences, limited access to certain search platforms, and other factors, that can affect the breadth and depth of the research.

2) External Threats: Data source reliability: Literature surveys may rely on information from various sources such as academic journals, conference papers, patent databases, etc. However, certain data sources may have issues of inaccurate information, biases, or lack of reliability, potentially affecting the credibility of your literature survey results. Threats from the limited dataset: the reference data used in RQ3. It is possible that the selected reference data may not sufficiently represent the diversity of driving conditions in all countries as the data sources range primarily focus on European literature.

VI. Conclusion & Future Work

Conclusion:

In this study, we have provided a comprehensive summary of the applications of SFCs in the field of autonomous driving as evidenced by academic platforms. These SFCs have primarily been used in spatial data processing, highlighting their effectiveness in handling large data sets. Furthermore, our research shows that SFC technology has already yielded promising results in data processing for autonomous driving.

Regarding our RQ2, we conducted an extensive literature review to investigate the current structure of various taxonomies. We also incorporated those selected taxonomies into a super taxonomy.

Regarding the third research question, we have employed a survey of existing literature coupled with kinematic parameter analysis. This approach has enabled us to discern the noteworthy kinematic parameters associated with distinct maneuvers. In light of these findings, we have proposed an indicator table. This table serves as a valuable point of reference during the process of filtering unprocessed data acquired from vehicular sensor sources. Additionally, it probably will facilitate the reduction of data dimensions when deploying the SFC technology.

Overall, our research aims to explore the latent capabilities of SFCs in the field of autonomous driving. At the same time, we aim to provide a detailed understanding of the present scenario-based and event taxonomies landscape.

Future work:

In future work, We expect to present the results of data analysis as a kind of feature map of spatial curves ”csp map”, which allows us to get the results of a vehicle's current specific event immediately based on a large amount of data, and the results must be intuitive enough for anyone to understand.

Moreover, there are several potential avenues for further investigation that could enhance our understanding of the subject. One such avenue is to explore SFC techniques and evaluate their effectiveness in various automotive scenarios. This would allow a more detailed analysis of the impact and potential benefits of different SFC approaches.

Additionally, future research should aim to expand the scope of analysis by exploring the relationships between indicators and maneuvers in greater depth. This could involve investigating the underlying mechanisms and factors that influence these relationships, as well as exploring additional indicator processing techniques that could provide further insights.

Finally, future studies could focus on evaluating the effectiveness of the proposed CSP approach in real-world scenarios. This could involve conducting field experiments or simulations to validate the findings and assess the practical implications of applying CSP techniques in different contexts.

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