Digital Twin for Driving

Erick Guerra (https://orcid.org/0000-0002-7769-2581)
Helen Loeb (https://orcid.org/0000-0001-5762-2044)

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Erick Guerra Zhanqian Wu, Luying Zhang, Jaime Hernandez, Chase Leibowitz, Helen Loeb, Xiaoxia Dong, Erick Guerra3, Rahul Mangharam

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16. Abstract

The use of digital mapping with precise GPS coordinates has allowed intelligent navigation, which is now ubiquitous in vehicles. The flat 2D imagery provided by Google maps was recently enhanced by the introduction of dynamic 3D representations of the Earth. Unity3D and Unreal Games Engines now offer Application Programming Interfaces that can be leveraged for geospatial applications. This technology, which offers visually compelling results for flight simulation and drone applications, opens new opportunities for driving simulation.This paper presents an innovative approach for developing a drivable Digital Twin of Philadelphia's Roosevelt Boulevard to enhance urban planning and traffic management using advanced simulation technologies. We introduce a complete pipeline that integrates geospatial imagery with data from Google Maps and OpenStreetMap (OSM) through tools like CityEngine and RoadRunner, enabling the creation of highly detailed, editable 3D urban scenes. This methodology facilitates rapid modifications to urban landscapes, exemplified by the integration of a bus lane into existing road infrastructure, demonstrating significant advancements over traditional methods. The core of our approach is a dynamic traffic flow model developed within the Unity driving simulator, utilizing probabilistic distributions and real-world data from the NGSIM dataset to mirror actual traffic conditions accurately. This model supports the simulation of realistic, varied, and dynamic traffic patterns, crucial for testing and evaluating urban traffic scenarios and infrastructure changes. The implementation showcases the potential of digital twins for transforming urban planning and traffic systems by providing a reliable platform for scenario testing and decision-making.

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1. Introduction

The integration of geospatial imagery into modern applications has significantly advanced in recent years, along with the driving application in digital twins for intelligent transportation systems. However, there are still challenges presented by the current state of technology, such as 3D model scarcity, time-consuming processes and limitations of non-editable 2D surface representations. This paper addresses the challenges by introducing a complete pipeline for developing a drivable Digital Twin for Philadelphia's Roosevelt Boulevard as a test case. Tile maps from Google Maps and OpenStreetMap (OSM) data are integrated with CityEngine and RoadRunner, to allow the construction of a vivid, editable scene for driving simulators. This pipeline includes data integration, static scene construction, alternative roadway layout demonstration and traffic dynamics evaluation. For the dynamic traffic evaluation, we introduce a traffic flow model which combines driving regulations and probabilistic distributions which are integrated into the Unity driving simulator. By leveraging the NGSIM dataset, we extract specific vehicle movement parameters and use them to develop a Gaussian distribution-based traffic model. This traffic model demonstrates the feasibility of our simulation, providing further information that can be used to improve the efficiency and safety of real dynamic traffic conditions.

2. Methodology

Current driving simulation softwares have two major limitations. First, creating accurate physical environments around roadways in driving scenarios is cumbersome. Second, the oversimplified and deterministic traffic flow models used in driving simulators might not accurately reflect real-world traffic situations and driving behavior.

The methodology developed below proposes an efficient pipeline for creating precise and vivid drivable scenes shown in Figure 1 and a traffic flow model that reflects different dynamic traffic conditions. In the first stage of the methodology, high-resolution tile maps of the target neighborhood are acquired through Google's maps ping services. These maps serve as a foundational dataset, which is then processed using a custom Python script designed to enhance resolution and clarify structural details, resulting in a comprehensive construction map. Subsequently, the process extracts detailed building outlines from OpenStreetMap (OSM), a collaborative project to create a free editable map of the world. This data is crucial for accurately defining the architectural boundaries and features of each structure. Using the extracted outlines, 3D models of the buildings are reconstructed with precision in CityEngine, a specialized software for urban environmental modeling, which offers realistic and scalable cityscape generation. The final phase of the workflow integrates the individually modeled buildings with the road infrastructure. This integration is achieved through a meticulous manual calibration process, ensuring that the spatial alignment and scale of roads and buildings harmonize seamlessly into a coherent and accurate 3D urban scene.

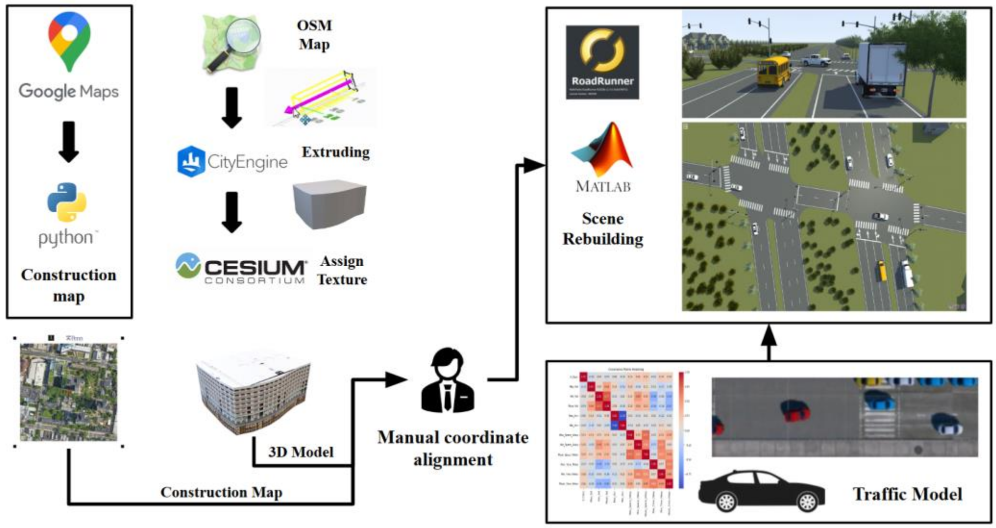

Figure 1: Pipeline for Developing Digital Twin.

2.1 Scene Construction

Our project leverages a synthesis of open-source data, sophisticated modeling techniques, and robust software platforms to construct intricate and lifelike scenarios for driving simulations. For the first step, we acquire original tile maps from Google Maps. A tile map is defined as a collection of pre-rendered, fixed-size images that depict map data across various zoom levels. A dedicated Python project was developed to automate the downloading of these tile maps, facilitating their transformation into high-resolution construction maps through advanced image processing techniques and parameter computation.

OpenStreetMap (OSM) is a collaborative initiative that provides an open-access, editable map of the globe. By harnessing data from OSM, we extract detailed building contours and associated terrain information, including elevation profiles. Our mapping accuracy is further augmented by integrating a texture database, which permits the random assignment of textures to each building model, thereby enhancing the visual richness and detail of the map representation. The resultant map visualization and various enhancements are depicted in Figure 2.

Figure 2: Examples of 3D Building Models Generation (Hospital of University of Pennsylvania)

For the second step, the refined blueprints are transformed into three-dimensional building models using the Cesium platform. During this phase, careful manual alignment of coordinates is performed to ensure spatial accuracy. In order to create a dynamic and realistic urban environment for driving simulations, we utilize Roadrunner, a versatile simulation tool developed by Matlab. This tool enables the crafting of vibrant, customized scenes tailored specifically for the requirements of driving simulations. Both the 3D building models and the high-resolution construction maps are imported into Roadrunner, where they are integrated to form comprehensive urban landscapes. Notably, this workflow allows for the efficient reconstruction of complex urban intersections, which can be completed in approximately 40 minutes. This rapid modeling capability significantly enhances the realism and detail of our simulations, thereby contributing to effective and life-like simulation of the driving experience.

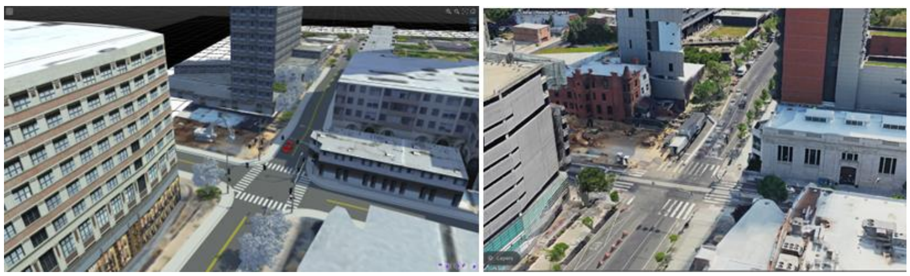

Figure 3: Scene Building: Scene Created in RoadRunner(left), Google Earth(right)

Once the scene has been completed in Roadrunner, it is exported to Unity for the creation of immersive scenarios. A detailed analysis of real-world traffic data underpins the development of a traffic flow model that accurately replicates diverse traffic conditions, including rush hour congestion and other time-dependent variations. By employing rule-based vehicles, we establish a dynamic traffic model that offer a realistic simulation of real-world dynamics. This methodical approach ensures the generation of authentic and realistic scenarios within Unity, facilitating extensive testing and analysis.

Our project exemplifies the seamless integration of various technologies and methodologies to enhance the efficiency of developing immersive driving simulations. Utilizing Python for image processing and data analysis, combined with the use of OpenStreetMap data and a texture database, we effectively create high-resolution construction maps and detailed 3D models. Roadrunner and Unity serve as advanced platforms for scene construction and scenario development, respectively, enabling the simulation of dynamic traffic environments with exceptional accuracy and fidelity.

2.2 Traffic Flow Model

The development of digital twins for intelligent transportation systems is gaining significant attention, primarily due to the challenge of creating simulations that effectively mirror realistic, varied, and human-like traffic patterns [1]. Such simulations offer a dynamic and innovative method for exploring traffic dynamics, revisiting traffic safety, and planning urban design.

A central objective within this context is to design seamless and coherent interactions between the autonomous vehicle (ego car) and other vehicles in its vicinity, while accurately replicating the complex behaviors characteristic of human drivers. This endeavor encompasses several layers of complexity, including the detailed interaction between road configurations and vehicle dynamics, and the nuanced understanding of driver preferences and societal interactions [2].

Although existing open-source traffic simulation platforms such as SUMO [3] and CARLA [4] have been instrumental in creating traffic flows, their reliance on oversimplified and deterministic driving models hinders their ability to fully encapsulate the intricacies and variability inherent in human driving behaviors. As a result, the traffic patterns generated by these tools often lack the diversity and subtlety needed, resulting in a uniformity that falls short of replicating the true nuances of human driving.

In the study presented, we introduce a novel approach for generating traffic flow, which leverages driving regulations and probabilistic distributions, effectively implemented within the Unity driving simulator. Initially, we extract vehicular movement characteristics and inter-vehicle interaction data from the NGSIM dataset [5]. Following a thorough data cleansing process, we identify and extract pivotal features pertinent to the traffic flow model, subsequently constructing a Gaussian distribution. In addition, we propose a set of fundamental principles for governing vehicle movement. The efficacy of the developed model is corroborated through validation exercises conducted on the Unity driving simulation platform, with empirical findings demonstrating that our method is capable of achieving a parametric and human-like representation of traffic flow.

2.2.1 Data Preparation, Feature Extraction, and Modeling

The NGSIM (Next Generation Simulation) dataset is a highly valuable resource in the field of traffic engineering and transportation research. It provides detailed vehicle trajectory data that captures the dynamic nature of traffic flow on selected road segments. The dataset encompasses high-resolution data on vehicle trajectories over specific time intervals, including detailed information such as the position, speed, and acceleration of individual vehicles, as well as lane changes and interactions between vehicles. This data was collected using video cameras mounted on elevated platforms, which monitored sections of highways and arterial roads at various locations within the United States.

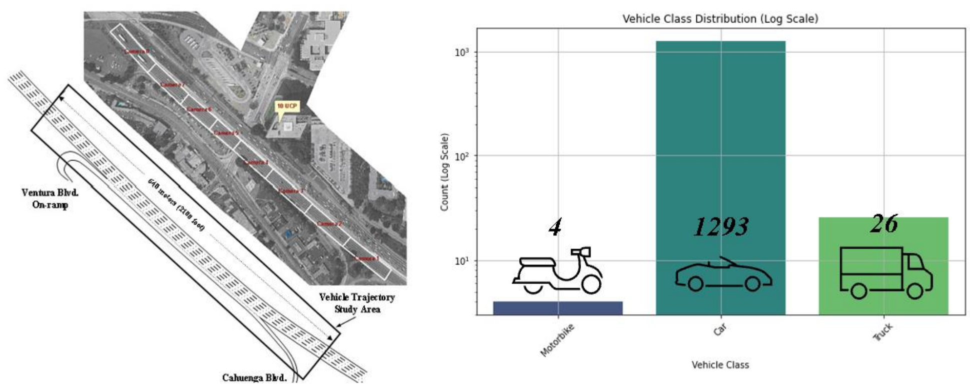

Figure 4: Data from US101 Highway (Collected during the time period of 8:20-8:35AM for a total of 1,323 complete vehicle tracks, of which, 1293 were car tracks, 26 were truck tracks, 4 were motorcycle tracks)

For our research project, as it is shown in Figure 4, data acquisition was carried out on the U.S. Highway 101 (a north–south highway that traverses the states of California, Oregon, and Washington on the West Coast of the United States.), with a focus on the time interval between 8:20 and 8:35 AM. This process yielded a comprehensive dataset that comprised 1,323 distinct vehicle trajectories, segmented into 1,293 car trajectories, 26 truck trajectories, and 4 motorcycle trajectories. Given the disproportionately small number of non-car trajectories, our analysis is exclusively concentrated on car trajectories, as the limited data on trucks and motorcycles do not suffice for a robust categorization within the scope of our study. This selective focus enables a more detailed and accurate exploration of car driving patterns, essential for the objectives of this research.

Rich of this empirical data, we proceed to design a stochastic model for car behavior. First, we determine which variables have a significant impact on the modeling of traffic flow by analyzing correlation coefficients. The correlation coefficient, represented by *r*, quantifies the degree and direction of a linear relationship between two variables. The formula for the Pearson correlation coefficient is shown as:

$$r = \frac{\sum(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum(x_i - \overline{x})^2 \sum(y_i - \overline{y})^2}}$$

where xi and yi are the individual sample points indexed with i.

The heatmap illustrated in Figure 5 represents a covariance matrix that represents the extent of co-variation among pairs of variables related to vehicle dynamics, as derived from data collected on the US101 freeway. The color spectrum within the heatmap, where red hues signify positive correlations and blue hues denote negative correlations, visually encodes the strength of these relationships. Values approaching 1 or -1 indicate strong positive or negative correlations, respectively, while values near 0 suggest a minimal linear relationship between the variables. One can infer from the analysis of the covariance matrix that there is a significant direct correlation between the average velocity (Mean_Velocity) of vehicles and their maximum velocity (Max_Velocity). Additionally, a substantial inverse correlation is noted between the minimum time headway (Min_Time_Hdwy) and the maximum velocity (Max_Vel). This relationship suggests that vehicles operating at higher speeds generally maintain greater time headways. Furthermore, the data reveals a pronounced negative association between the mean time headway (Mean_Time_Hdwy) and the mean velocity (Mean_Velocity), underscoring the dynamic interplay between speed and spacing on the freeway.

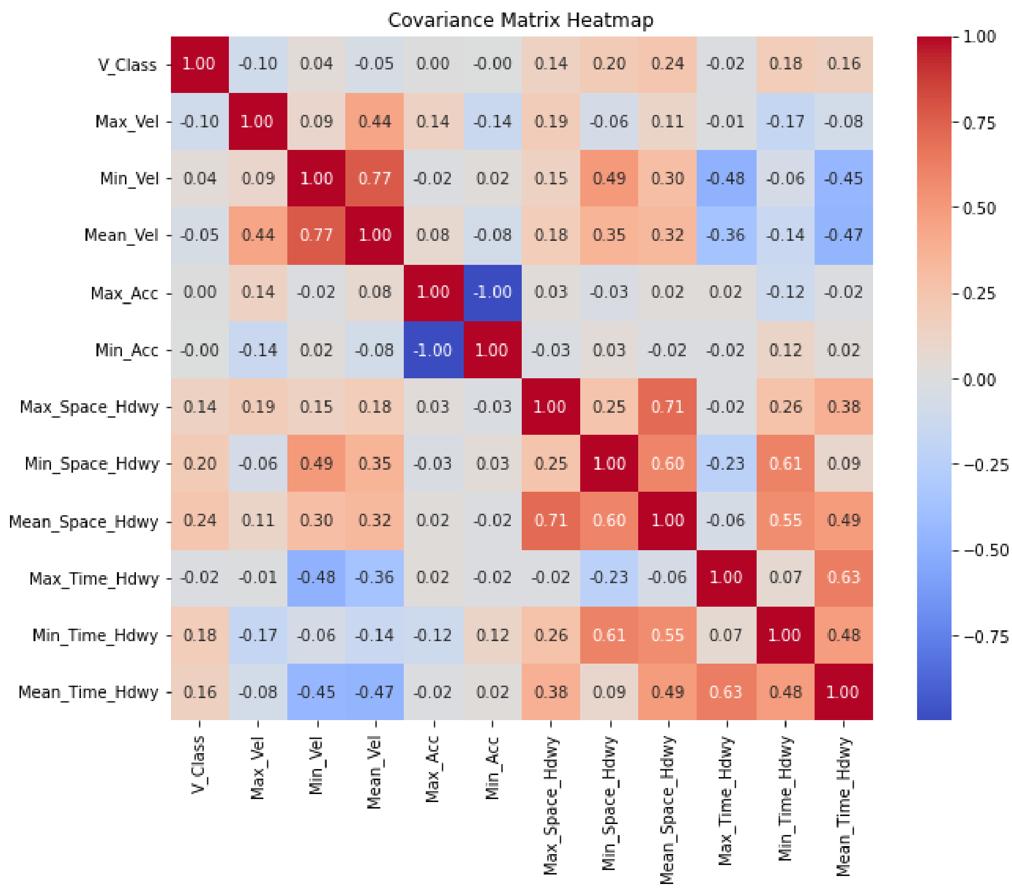

Figure 5: Covariance Matrix Heatmap Illustrating the Interrelationships Among Vehicle Dynamic Parameters on US101 Freeway During Morning Peak Hours

Figure 6 provides a comprehensive analysis of vehicle velocity distributions. The mean vehicular speeds are graphically represented through a green curve, which closely approximates a Gaussian distribution, centered around 25 miles per hour. This central tendency suggests that the average velocity observed across vehicles predominantly stabilizes at this value. Such a distribution implies a typical flow condition under normal traffic states. In contrast, the minimum velocities, depicted in red, exhibit a distribution that is markedly skewed towards lower velocities. The density curve peaks near zero, indicating a frequent occurrence of very low speeds, which might be reflective of congestive traffic conditions or idling vehicles. On the other hand, the maximum velocity distribution, illustrated in blue, appears to follow a Gaussian shape but with a peak around 45 miles per hour. This distribution suggests that higher velocities are not uncommon but are bounded, likely due to traffic regulations or road conditions that limit maximum speed.

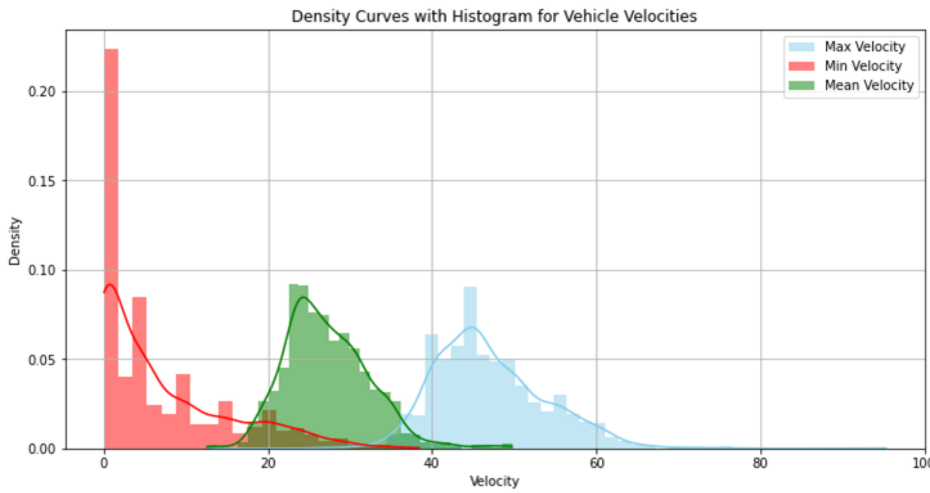

Figure 6: Comparative Density Distribution of Maximum, Minimum, and Mean Vehicle Velocities on a Freeway

Figure 7 depicts the density and frequency distributions of minimum and mean time headways in freeway traffic, with the x-axis specifying the time headway in seconds and the y-axis denoting the density. Time headway is a critical concept in traffic engineering, defined as the time interval between two consecutive vehicles as they pass a fixed point on a roadway. Mathematically, it can be expressed as:

$$TH = \frac{T_{n+1} - T_n}{1}$$

where

- TH is the time headway,
- T_{n+1} is the timestamp when the following vehicle passes the reference point.
- T_n is the timestamp when the leading vehicle passes the same point.

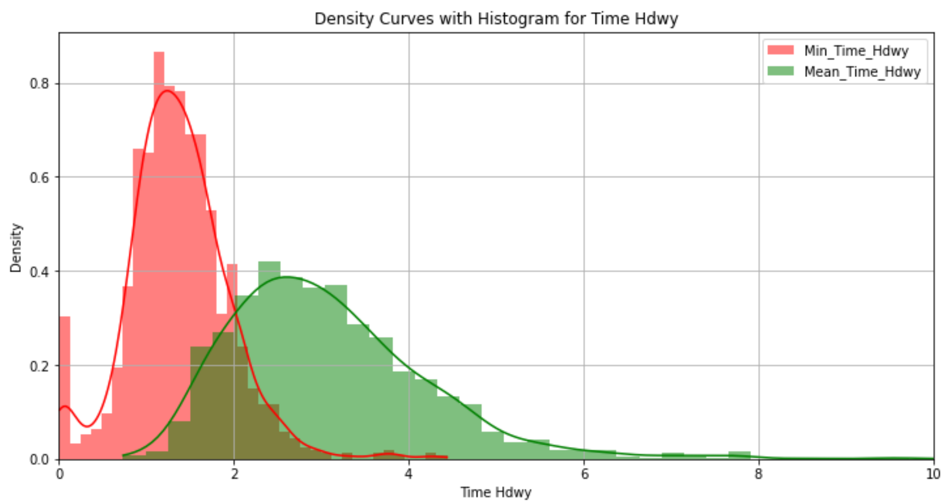

Figure 7: Distribution Analysis of Minimum and Mean Time Headways on Freeway Traffic

Conditions

This metric is essential for assessing traffic flow and density, and is particularly useful for determining roadway capacity, designing signal timings, and evaluating the performance of transportation systems. A shorter time headway implies higher traffic density and possibly congested conditions, while a longer time headway indicates lower density, which may correspond to free-flowing traffic. Understanding the distribution of time headways across a network can help traffic engineers and planners optimize traffic movement and enhance road safety [6].

The analysis of the time headway distributions within vehicular traffic reveals distinctive patterns. The mean time headway distribution (depicted in green) exhibits a Gaussian-like profile with an apex at around 2.5 seconds. This infers that, on an average scale, the temporal distance between vehicles is typically around 2.5 seconds, with the likelihood diminishing for larger headway intervals.

In contrast, the minimum time headway data (represented in red) predominantly congregates at the lower end of the spectrum, indicating a preponderance of instances where vehicles follow each other at minimal temporal gaps. This characteristic is symptomatic of dense traffic where brief headways are common, perhaps indicative of congested driving conditions or aggressive driving behavior.

From the above analysis, we find that traffic flow dynamics can be modeled through a bi-variate Gaussian distribution framework, which incorporates a quartet of pivotal variables: Maximum Velocity, Mean Velocity, Minimum Time, and Mean Time Headway.

$$f(x, \mu, \Sigma) = \frac{1}{(2\pi)^2 |\Sigma|^{1/2}} exp(-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu))$$

$$\Sigma = \begin{bmatrix} 47.368302 & 15.706657 & -0.682055 & -0.643502 \\ 15.706657 & 26.809399 & -0.429600 & -2.839082 \\ -0.682055 & -0.429600 & 0.340115 & 0.331012 \\ -0.643502 & -2.839082 & 0.331012 & 1.378618 \end{bmatrix}$$

$$\mu = \begin{bmatrix} 47.001988 \\ 27.229243 \\ 1.374084 \\ 3.092426 \end{bmatrix}$$

where:

- $\mathbf{x}$ is a 4-dimensional column vector representing the variable of interest.
- μ is a 4-dimensional column vector representing the mean of the distribution.
- Σ is a 4×4 covariance matrix that characterizes the spread and the correlation of the variables in the distribution.
- $|\Sigma|$ is the determinant of the covariance matrix Σ.

This statistical approach enables the encapsulation of both the extremities and the central tendencies of vehicular movements and temporal spacing on thoroughfares.

2.2.2 Basic Traffic Rules

In modeling vehicular behavior within a simulated traffic environment, five fundamental principles are postulated:

a) Vehicle attributes are determined through a stochastic process that involves random sampling from a Gaussian distribution, providing a foundational basis for individual vehicle characteristics.
b) The algorithm governing each vehicle stipulates that it should operate at the highest possible velocity, in adherence to prevailing traffic conditions and within the constraints of safety regulations.
c) Continuous environmental scanning is mandated for each vehicle during every frame of simulation. Should the presence of an obstacle or the signal of a red traffic light be detected, the vehicle is required to decelerate.
d) In instances where the velocity of a preceding vehicle is lower than that of the following vehicle, the latter is programmed to maintain its course for a predefined number of frames, subsequent to which it will execute a lane change to facilitate overtaking.
e) Upon the occurrence of a collision, the implicated vehicle is programmed to be virtually eliminated from the simulation after the lapse of a specified number of frames, thus simulating the aftermath of an accident.

These rules aim to replicate realistic traffic flow and vehicle interactions, enhancing the authenticity of the traffic simulation.

3. Analysis and Results

3.1. Traffic Flow Simulation on Unity Driving Simulator Platform

In the context of our research, we applied our software to validate its effectiveness in real-world scenarios by undertaking a quick streetscape modeling project on Roosevelt Boulevard, PA, as detailed in Figure 8 (a). This specific application involved the integration of a bus lane into the existing infrastructure of Roosevelt Boulevard. Traditionally, such an integration would require extensive time commitments and resources due to the complexities associated with modifying urban roadways. However, the utilization of our innovative software significantly expedited this process. The proposed addition of a bus lane, illustrated in Figure 8 (b), was executed to demonstrate the software's capability in swiftly adapting roadway plans to include additional transportation modalities. This feature of the software is particularly critical in urban planning and civil engineering, where rapid prototyping of traffic scenarios and infrastructural changes is essential for effective decision-making and planning.

Our software's ability to rapidly model and integrate a bus lane into the existing roadway system of Roosevelt Boulevard showcases its potential as a transformative tool in urban transportation planning. It facilitates a more dynamic and responsive approach to urban design, where modifications can be implemented and assessed in real-time, significantly reducing the turnaround time traditionally associated with such projects. This capability not only enhances the efficiency of urban planning processes but also contributes to more sustainable and adaptable urban environments.

Figure 8: A quick streetscape modeling of Roosevelt Blvd; (b) a hypothetical scenario of adding a bus lane

3.2. Traffic Flow Algorithm Tuning

For our research project, we employed a Unity-based simulation environment for the rigorous evaluation of our traffic flow generation algorithm. The Unity 3D game engine offers solid rendering capabilities, comprehensive physics modeling, and proficiency in real-time 3D simulations. This platform was deliberately chosen for its high fidelity in mimicking real-world traffic scenarios, thereby providing a robust framework for our experiments.

Figure 9: Comparative Visualization of Traffic Flow Density and Average Velocity in a Unity-Based Simulation

Figure 9 serves as a visual representation of our experimental setup. Within this framework, we systematically altered the parameters pertaining to vehicular speeds and traffic flow densities. These modifications allowed us to assess the adaptability and resilience of the traffic flow generation algorithm across a spectrum of traffic conditions.

The results of these tests, graphically depicted in Figure 9, provide a visual illustration of the algorithm's performance. They highlight the algorithm's capability to generate realistic and dynamically varied traffic patterns. The outcomes not only corroborate the algorithm's operational effectiveness but also highlight its precision in simulating an array of traffic conditions with notable accuracy. The ensuing figure succinctly encapsulates these findings, affirming the algorithm's proficiency in replicating diverse traffic scenarios within the simulated environment, thereby underscoring its potential utility in real-world applications.

4. Discussion

This paper describes the development and application of a novel pipeline for constructing a drivable Digital Twin (DT) for Philadelphia's Roosevelt Boulevard. Utilizing advanced geospatial imagery and a combination of urban planning tools, including CityEngine and RoadRunner, integrated with tile maps from Google Maps and data from OpenStreetMap, we have successfully demonstrated a methodology that accelerates the modification of urban landscapes in digital environments. This is particularly evident from the rapid integration of a bus lane into the existing roadway system, a task that traditionally involves considerable time and resource commitments.

Our approach has significant implications for urban planning and traffic management, especially in addressing the challenges associated with urban traffic flow and safety. Roosevelt Boulevard, known for its hazardous traffic conditions, served as an ideal case study for applying our DT workflow. The ability to quickly iterate and simulate various traffic scenarios can lead to better-informed decisions in urban development and infrastructural modifications, potentially reducing traffic fatalities and improving road safety. Moreover, the use of Unity for simulating traffic dynamics provided a robust platform for testing and validating our traffic models against realistic traffic conditions. This facilitated not only the visualization of traffic patterns but also the assessment of potential interventions in a controlled virtual environment. The simulation results highlighted the effectiveness of the traffic flow model in replicating diverse traffic conditions, thereby offering a promising tool for traffic engineers and planners. The implications of our study extend beyond traffic management. The methodology employed can serve as a blueprint for other cities aiming to enhance their transportation systems or to test infrastructure changes before implementation. Additionally, the flexibility and scalability of the DT approach mean that it can be adapted to various urban and traffic conditions, making it a versatile tool in the broader field of urban planning.

Despite the advancements demonstrated in this study, there are limitations that must be acknowledged. One significant limitation is the reliance on available geospatial and traffic flow data, which may not always be updated or comprehensive enough to capture the complex dynamics of a real-world environment. Additionally, the computational demand of simulating detailed traffic scenarios at high fidelity remains a challenge, particularly when scaling up to larger urban areas. Moreover, while the Unity platform provides robust capabilities for traffic simulation, the current traffic models still rely on approximations and may not fully capture the unpredictability of human driving behaviors. Further refinement of the traffic models is required to enhance their predictive accuracy and realism. Future research will focus on several key areas to address these limitations:

(1) Data Integration: We plan to incorporate real-time data feeds into our simulations to enhance the responsiveness and accuracy of our traffic models. This includes live traffic updates, weather conditions, and other dynamic factors affecting traffic flow.

(2) Model Complexity: Efforts will be made to develop more sophisticated traffic models that better mimic human driving behaviors and interactions. This involves the integration of machine learning techniques to predict and simulate more complex traffic scenarios.

(3) Multi-Modal Transportation: Future studies will include the modeling of multi-modal transportation systems within the DT to reflect the increasing diversity in urban mobility solutions, such as public transit, cycling, and pedestrian pathways.

5. Conclusion

In conclusion, the development of a drivable Digital Twin using our proposed pipeline represents a significant advancement in the field of urban planning and traffic simulation. By enabling rapid and accurate modeling of urban traffic scenarios, our approach aids in the efficient planning and safe management of urban roadways. As we move forward, the integration of more dynamic data sources and advanced modeling techniques will further enhance the utility and accuracy of digital twins, paving the way for their broader adoption in urban development and traffic management initiatives.

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