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PROCESSING OF GEOSPATIAL DATA FOR AUTONOMOUS VEHICLES

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Abstract

The capability of autonomous vehicles has been progressing at a great rate and is expected to continue to do so. Trials and research to date has focused on technological performance and operations, with further work around safety, regulation and the human-machine interface. In order to make safe driving decisions, autonomous vehicles need reliable geospatial information to assist them in any situation, such as knowing road layouts, what obstructions may lie ahead, and updates about local traffic laws. The function of the mapping module is to provide a geospatial data to support autonomous driving by storing information on the environment, allowing vehicles to understand the world that surrounds them.

Keywords— Geospatial Data, Driverless Vehicles, SDFE ,Machine Learning, CAV ecosystem

I. INTRODUCTION

Geospatial data is all about objects, or the phenomena that have a particular location on the surface of the earth. This location could be the road location or an earthquake or children who are living in poverty. The geospatial data combines all of this information and also the coordinates of the earth so that the temporal information even exists. Whether collected by public or private organizations, large amounts of geospatial data are available as open data. This means that it can be accessed freely by users, and is made available through open standards.

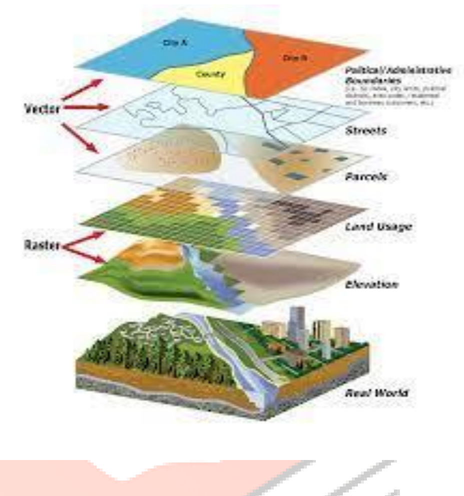

Fig 1: Geospatial Data

The data management challenges of the most advanced conventional automobile manufacturing are mirrored in the design and operation of driverless vehicles, but at a different magnitude. Aggregation of these different types of environmental data affords driverless cars a reliable picture of their environment, and poses a potential challenge to data management. The constantly shifting pathnames for files associated with the hardware refreshes and manual selection of storage locations associated with traditional data management methods create inefficiency in engineering processes.

However, the potential to cause problems of safety and efficiency when driverless cars move beyond the closely monitored experimental stages of development is even greater. In addition to the challenges to data access, driverless cars rely on disparately collected and stored datasets. Eventual widespread adoption of driverless cars will almost certainly involve inter-vehicle data sharing and communication that will make ease of data access even more critical. Avoiding these barriers to data access will require use of a data management system that can insulate data users from changes to hardware. These IT upgrades and refreshes are necessary, but need not interfere with data access. A successful approach to managing this data will include virtualization that can separate the hardware on which data is stored from the system that keeps track of where it is stored, so that pathnames remain unchanged and storage can be scaled up as needed. Abstraction offers the possibility of a unified namespace for storing critical and diverse datasets together, which makes aggregation simpler

Real-time access will require fast and relatively expensive storage media such as flash storage. With virtualization those data can be automatically moved to less-expensive media, such as disk, as their value shifts from offering information for real-time decision-making to safety and design analysis months, years, or decades later. Software design, safety, and maintenance improvements are well-served by a system where data on vehicle behavior and safety remain accessible in the long run.

II. OBJECTIVES

With this project we aim at:

- Effective management of Geospatial Data
- Efficient integration of Geospatial Data in autonomous vehicles
- Designing standard data format and structure for all autonomous vehicles.

III. LITERATURE SURVEY

The capability of self-driving cars has increased substantially in recent years, and is expected to be an important part of the fleet within the next decade. These vehicles can be thought of in two different ways – connected vehicles and autonomous vehicles. Connected vehicles (CV) allow vehicles to communicate with each other and the world around them. This concept is often about supplying useful information that can inform decision making – it does not necessarily imply that the vehicle is “making” choices for the driver. These sorts of technology are already well embedded in the vehicle fleet, for example with GNSS-based navigation systems often including dynamic route guidance. Autonomous vehicles (AV) remove some or all tasks from human control. The level of automation in a vehicle may vary, ranging from minor “assistance” to the driver, to a fully automated vehicle that does not require a driver to function. Some of these technologies are market ready and available to users, including self-parking, lane-keep assist, and emergency braking systems. These technologies are often described using the SAE International Standard, describing vehicles from Level 0 (No automation) to Level 5 (Full automation). The Danish Geospatial Agency (SDFE) supplies citizens and business with reliable data, giving information about infrastructure and society. An important part of the role of SDFE understands the requirements placed on its data, and undertaking a program of continuous improvement to ensure benefits from data provision are maximized. It is therefore essential for SDFE to understand the potential requirements for geospatial data to support the operation of autonomous vehicles.

For the last decade, the progress made in the autonomous driving scientific community and industry has been exceptional. With the rise of deep-learning and better hardware, algorithms embodying the different aspects of driving, such as lane following, obstacle detection, semantic segmentation, tracking, and motion estimation have reached unprecedented performance. Although there are still no SAE Level-4 self-driving vehicles as of yet, recent developments in robotics and machine learning could soon make this aspiration a reality. The availability of training data is a critical factor to the growth and success of autonomous driving. Although more powerful than traditional machine learning techniques, deep learning algorithms require a particularly massive amount of data for training and testing purposes. Moreover, in order to assimilate the entire driving process complexity and be reasonably safe, algorithms need to account for all possible real world scenarios, thus demanding highly dynamic and diverse datasets. Finally, it is often dangerous, costly and time-consuming to test driving algorithms on real vehicles.

IV.EXISTING PROBLEMS

Forecasting technological change is a difficult undertaking. Several studies have sought to do this for CAVs, both in terms of sales and proportion of the vehicle fleet. This requires a series of assumptions, including cost, technological availability, public acceptance, and the necessary regulations. There are clear and expected trends around the adoption of low level automation technologies with a growing share of the new vehicle fleet. Significant uncertainties remain on the evolution of the CAV penetration. Those uncertainties can be explained by the following impacting factors :

- **Regulation** – the pace of change is slower than technological advancement, potentially slowing down the introduction to market. Regulatory bodies may also impose restrictions on CAVs (such as mandating segregated corridors) and therefore impact the ‘supply’ of CAVs;

- **Liability** – there is currently no agreement on responsibility in case of incidents;

- **High cost** – as an emerging technology, CAVs may be prohibitively expensive in the short term, limiting uptake on a large scale;

- **Consumer acceptance** – there is a potential lack of trust from consumers, and an underlying “desire to drive” that may prevail;

- **Security** – with potential concerns that security systems are not sufficient to permit higher level functionality;

- **Human machine interaction (HMI)** – a specific concern around partially automated vehicles , which may not enter the market due to the risk of drivers not monitoring the road, but expected to resume control at any time; and,

- **Political and social factors** – with concerns over job protection and labour risks due to automation.

V. WORKING MODEL

Data Collection:

In this particular step the Data collection process will be carried out as per the need. The Data may be structured or unstructured. And the data collected will be converted into semi structured data.

Pre Processing of Data:

The main aim of pre processing data is to remove Null Values, Finding the Mean and Median etc.

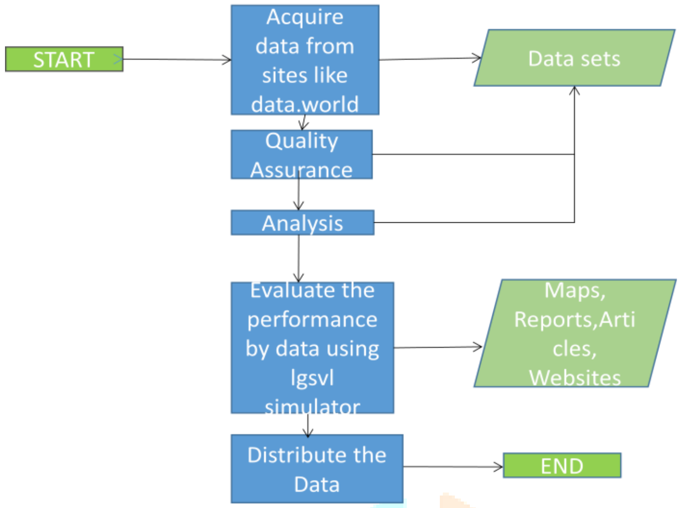

Fig 2: Activity Diagram

Data Loading:

The Structured or Unstructured or Semi Structured Data will be loaded. The Loaded data will be converted into Cured Data Sets for further processing.

Data Analysis:

The Data Sets will be analyzed and processed whenever it is needed. To do this analysis the existing techniques or algorithms will be used. For example to know the nearest vehicle the KNN algorithm will be applied to extract the analytics.

Performance Evaluation:

The system will be evaluated based on the resource conception and expected outcome.

Algorithms:

Geo MLP - Multilayer Perceptron Neural Network, training using 1st and 2nd order gradient training algorithms

Geo GRNN - General Regression Neural Network with 6 types of kernels, cross-validation tuning of parameters, automatic detection of anisotropy

Geo KNN - k-Nearest Neighbour algorithm for regression and classification

Geo SVM - Support Vector Machines/Regression, equipped with two conventional QP solvers and tools for tuning the hyper-parameters, visualisation of support vectors

Geo MDN- Mixture Density Network, based on Radial Basis Function Neural Network is a valuable tool for real risk mapping.

Geo MISC - utilities to perform exploratory data analysis, to manage and to visualise data

Data mining in a high dimensional geo-feature space- machine learning (supervised and unsupervised learning algorithms)

VI. CONCLUSON

The key conclusions of this system are:

• **Geospatial data is important** – CAVs will need to have an understanding of the environment around them. Whilst an element of this will be achieved through on-board sensors, geospatial data and base mapping will likely be essential. Geospatial data is already a crucial enabler for a variety of CAV trials, and this is likely to continue.

• **The quality of geospatial data will impact the efficiency, effectiveness and benefits of CAVs** – benefits to consumers, network operators and infrastructure providers will be enhanced through accurate, reliable and comprehensive geospatial and mapping data. This is a potentially important role for public sector organizations such as SDFE – ensuring the right data is available to maximize societal benefits, and implementing standards to ensure a minimum level of service.

- **Private geospatial data companies are active** – the market is reacting to the need for this data, ensuring the requirements for CAV operation are available. The automotive industry is committed to the introduction of autonomous vehicles. Where geospatial data is a key requirement of CAV operations, the private sector has also demonstrated a willingness to provide these data. This is best illustrated by the acquisition of mapping company HERE by a consortium of German car makers.

- **Data held by SDFE and other agencies potentially has great value** – but there are recognized issues with precision, coverage, access and conformity that may limit application. It is also recognized that there is no single repository for geospatial data for roads in Denmark, and no clear owner of standards and regulation.

- **There is an important gap in the emerging CAV ecosystem** – in order to facilitate the operation of connected and maximize the benefits for society. SDFE are well-placed to enable and establish a scalable and flexible geospatial data platform, capable of ingesting, aggregating and distributing data both from and for autonomous vehicles. SDFE are also ideally placed to drive development of standards and data and reference models that will be required to ensure consistency in data, again ensuring that the societal benefits of CAVs – for congestion, environment and safety – can be realized.

VII. EXPECTED OUTCOMES

- 90% reduction in traffic deaths
- 60% drop in harmful emissions
- 10% improvement in fuel economy
- Consumer savings of 5 billion euro
- 40% reduction in travel time
- 500% increase in lane capacity

VIII. SCREENSHOTS OF RESULT

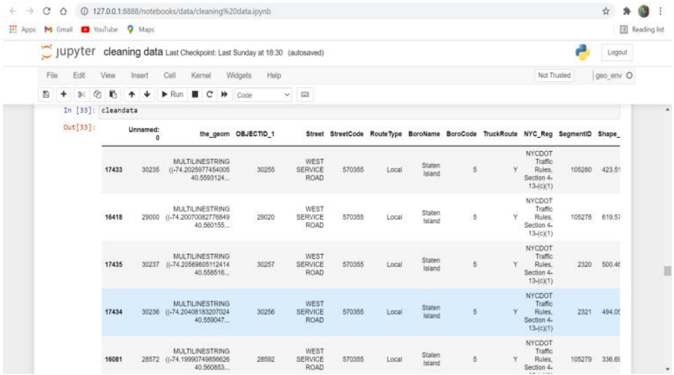

Fig 3: Cleaned Data

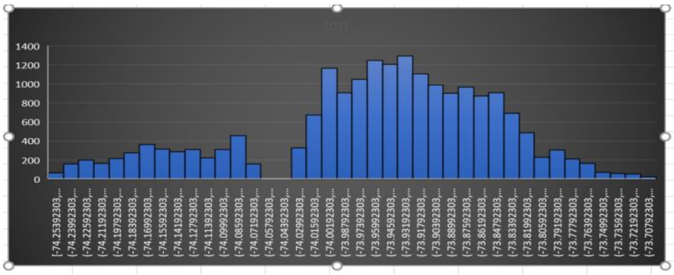

Fig 4: Visualization of clean Data

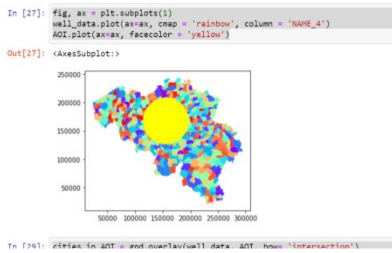

Fig 5: Intersection of Shapefiles

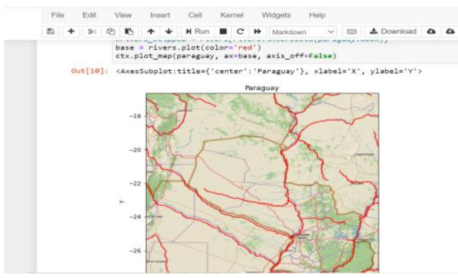

Fig 6: Visualization of Shapefiles

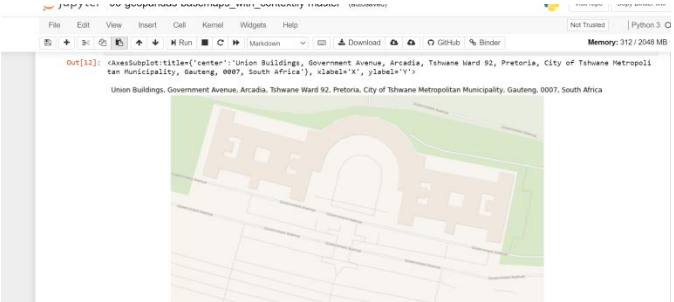

Fig 7: Final Road map of processed data

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