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Multi-Source Data Integration for Navigation in GPS-Denied Autonomous Driving Environments

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ABSTRACT- Autonomous driving is making rapid advances, and the future of driverless cars is close to fruition. The biggest hurdle for autonomous driving currently is the reliability and dependability of navigation systems. Navigation systems are predominantly based on GPS signals and despite it being highly available there are scenarios where GPS is either not present or unavailable such as in tunnels, indoor environments, and urban areas with high signal interference. This paper proposes an adaptive decision-making algorithm that leverages multi source data source integration for navigation in GPS-denied environments. The algorithm enables seamless switching between the different data sources such as LTE or 5G for autonomous driving systems to maintain accurate navigation even when GPS signals are unavailable. Overall, this approach represents a sound methodology for developing navigation systems that can reliably support autonomous driving applications in real-world conditions.

Keywords: GPS, cellular, navigation, autonomous driving, 5G, LTE.

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1. INTRODUCTION

Autonomous driving systems (ADS) are being designed, developed and tested at a rapid rate and there are a lot of expectations from both consumers and governmental organizations. This is mainly due to the promises of safer driving, reduced accidents, improved traffic navigation and lower emissions [1]. For instance, in the USA alone, there were a total of 39508 car fatalities in the year 2021 [2].

The main requirement for autonomous vehicles to fulfil the expectations is their ability to navigate reliably and accurately in various environments. Global Positioning System (GPS) has been the main building block for navigation systems, providing precise location information through satellite signals [3]. However, GPS signals can be prone to disruptions, particularly in urban canyons, tunnels, and adverse weather conditions, posing challenges to autonomous driving systems.

There are several situations and environments where GPS signals may be unavailable or unreliable:

1. *Urban Canyons*: GPS signals are often blocked by high rise buildings in vehicles equipped with onboard GPS receivers which form the urban canyon environments.
2. *Tunnels*: The enclosed nature of tunnels can block GPS signals, leading to GPS based navigation problems.
3. *Indoor Environments*: GPS signals generally cannot penetrate buildings sufficiently, making navigation difficult or impossible indoors.
4. *Dense Forests*: GPS signals are easily affected by thick trees and foliage resulting in signal loss or lower accuracy.
5. *Urban Areas with Signal Interference*: Interference from buildings, vehicles, or other electromagnetic sources can degrade signal quality.
6. *Underground Parking Garages*: The structure and materials of underground parking facilities can block GPS signals.
7. *Harsh Weather Conditions*: Heavy rain, snow, or storms can interfere with GPS signals, reducing accuracy.
8. *Remote Locations*: In areas with limited infrastructure or in wilderness settings, GPS coverage may be sparse or non-existent.
9. *Jamming and Spoofing*: Deliberate interference through jamming or spoofing attacks can disrupt GPS signals, affecting navigation systems. [4-11]

In scenarios where GPS signals are unavailable or unreliable, autonomous vehicles must immediately rely on alternative sources of data for navigation. To address this need, this paper proposes an adaptive decision-making algorithm designed to enable autonomous driving systems to seamlessly transition between different data sources in GPS-denied environments. By integrating multiple data sources, such as Long-Term Evolution (LTE) or 5G networks, into the navigation system, the algorithm aims to maintain accurate and continuous navigation capabilities even when GPS signals are unavailable.

Unlike existing solutions that rely primarily on a single alternative navigation method in GPS-denied environments, our approach uniquely integrates multiple data sources through an adaptive decision-making algorithm. This system dynamically switches between GPS and cellular network-based navigation, providing a more robust and continuous navigation solution. Our method improves upon existing techniques by offering seamless transitions between navigation modes, adapting in real-time to changing environmental conditions, and leveraging historical data to optimize decision-making.

The key idea behind the proposed algorithm is to dynamically assess the availability and quality of alternative data sources and select the most reliable option for navigation based on real-time environmental conditions. This adaptive decision-making process allows autonomous vehicles to adapt to changing circumstances and ensure safe and efficient navigation in GPS-denied scenarios.

The rest of the paper is organized as follows. *Section 2* comprehensively covers the current literature and related work, providing insights into existing research on autonomous navigation systems and GPS-denied navigation techniques. *Section 3* delves into the specifics of our system architecture, highlighting the design rationale and operational idea behind the decision-making algorithm. *Section 4* lists the system's limitations offering a thorough examination of its constraints. *Section 5* outlines future research directions, providing brief ideas for next steps in improvement. Finally, *section 6* concludes our findings and contributions, offering reflections on the broader implications of our work.

2. RELATED WORK

Durrant-Whyte and Bailey demonstrated the use of simultaneous localization and mapping (SLAM) techniques to enable autonomous vehicles to navigate unknown environments by simultaneously constructing a map of the surroundings and estimating the vehicle's location within that map [12].

Mur Artal et al. presented a real time operation feature based monocular SLAM system that works in both small and large indoor and outdoor environments using the same features for all SLAM tasks: tracking, mapping, relocalization, and loop closing. Visual-inertial navigation systems combine visual and inertial sensor data for robust navigation in GPS-denied environments [13].

Liu et al. surveyed all the existing wireless indoor positioning solutions and work in different classification systems. The paper analysed three major location estimation schemes of triangulation, scene analysis and proximity [14].

While these existing solutions offer valuable approaches to navigation in GPS-denied environments, they each have limitations. SLAM techniques [12, 13] can be computationally intensive and may struggle in featureless environments. Visual-inertial systems [13] are susceptible to errors in low-light conditions. Wireless indoor positioning solutions [14] are often limited to specific, pre-mapped areas. Our proposed system addresses these limitations by combining multiple data sources and employing an adaptive decision-making algorithm, allowing for more flexible and robust navigation across various environments.

Bachrach et al. presented a solution to address the problem of autonomous navigation for micro air vehicle (MAV) in GPS-denied environments. They presented experiment-based validation for a system that enables a quadrotor helicopter, equipped with a laser range finder sensor, to autonomously explore and navigate unknown environment [15].

Kassas et al. presented a solution that uses signals of opportunities (SOPs) In environments where GPS signals are challenged or denied. This article presents how SOPs could help materialize a radio simultaneous localization and mapping (radio SLAM) approach for reliable and accurate positioning, navigation, and timing (PNT) source [16].

3. SYSTEM ARCHITECTURE

The adaptive navigation system for autonomous vehicles ensures continuous and reliable navigation by seamlessly transitioning between GPS and cellular network (LTE/5G) navigation modes based on signal availability and strength. It primarily relies on GPS signals for positioning and navigation but activates a fallback mechanism to switch to cellular network navigation if GPS signals are unavailable or unreliable. The system continuously monitors signal strength, initiates navigation mode switches when necessary, and ensures smooth transitions between GPS and cellular network navigation modes. By dynamically adapting to changing signal conditions, the system enhances navigation and overall safety in various environments.

The novelty of our system lies in its adaptive decision-making algorithm. Unlike traditional systems that rely on fixed thresholds, our algorithm dynamically adjusts its parameters based on real-time signal quality assessments and historical performance data stored in the cache memory. This approach allows for more nuanced and context-aware decisions, improving the system's ability to maintain accurate navigation in challenging and changing environments.

3.1. System Components

3.1.1. GPS Receiver

The GPS receiver is the primary source of data for vehicle positioning and navigation data. It receives signals from satellite constellations orbiting the Earth and calculates the vehicle's precise location coordinates, speed, and direction. This is done based on the time it takes for signals to travel from the different satellites to the receiver. Opting for a high-precision GPS receiver, namely the NovAtel OEM7 series GNSS receiver, was driven by its advanced features and reliability [17, 18]. Each feature of the GPS receiver is analysed and listed in *table 1*.

Table 1. Analysis of GPS receiver

Feature	Description
Receiver Type	Supports multiple global navigation satellite systems (GNSS) including GPS, GLONASS, Galileo, and BeiDou. Multi-frequency operation enhances accuracy and robustness, especially in challenging environments.
Performance	Provides centimeter-level positioning accuracy in real-time, making it suitable for critical applications such as autonomous driving. High advanced signal processing algorithms for ensuring reliable satellite signal reception even in obstructed or poor-signal environments.
Features	Supports dual-antenna configurations for precise direction determination and altitude estimation. Utilizes advanced signal tracking technologies to mitigate multipath/interference effects.
Connectivity	Supports various communication protocols including RS-232, RS-422, USB, and Ethernet for seamless integration with vehicle onboard systems. Supports real-time kinematic (RTK) and precise point positioning (PPP) techniques for improved accuracy in challenging navigation scenarios.
Durability and Environmental Specifications	Designed to endure sever environmental conditions such as high and low temperature, humidity, and electromagnetic interference.
Scalability and Customization	Offers configurable software and hardware options for seamless application integration. Provides scalability in performance and functionality that enables customization and optimization based on the needs of the autonomous vehicle navigation system.

3.1.2. Cellular Modem

The inclusion of a cellular modem complements the capabilities of the GPS receiver by providing an alternative source of location data through LTE or 5G networks. When GPS signals become unavailable, cellular networks can take over to provide coverage. By leveraging cellular technology, the system can maintain continuous access to location data even in GPS-denied areas. Additionally, cellular networks can provide additional data such as traffic information, road conditions, and map updates, enhancing the overall navigation experience. A suitable option for the cellular modem is the Sierra Wireless AirLink RV50X Industrial LTE Gateway, known for its rugged design, advanced features, and wide range of connectivity options [19, 20]. Each feature of the cellular modem is analyzed and listed in *table 2*.

Table 2. Analysis of Cellular Modem

Feature	Description
Cellular Connectivity	Provides support for LTE and 5G, offering high-speed data rates and low-latency communication. Supports multiband LTE and multiple cellular standards, ensuring compatibility with network infrastructures globally.
Performance and Reliability	Delivers real-time communication and data transfer vital for safety critical navigation.
Features	Offers dual SIM slots for redundancy and failover, ensuring continuous connectivity by automatically switching between cellular networks or providers in case of signal loss or network outage. Includes remote management capabilities for configuration, monitoring, and firmware updates over-the-air (OTA), simplifying device management and maintenance.
Durability and Environmental Specifications	Withstands diverse environments including extreme heat and cold, humidity, and shock. Features an IP64-rated enclosure for protection against dust, water, and other environmental debris.
Connectivity and Interfaces	Provides Ethernet and serial connectivity options for seamless integration with onboard systems, sensors, and controllers. Includes GPIO ports for interfacing with external devices and sensors.
Security and Compliance	Incorporates advanced security features such as secure boot, VPN and IPsec ensuring secure communication and data protection. Meets industry and regulatory requirements for cellular communication such as FCC, PTCRB, and CE.

3.1.3. Decision-Making Algorithm

The decision-making algorithm continuously evaluates the availability and signal strength of GPS and 4G/5G cellular signals along with other parameters such as vehicle speed and navigation objectives. The algorithm then dynamically chooses between GPS-based navigation and cellular-based navigation to ensure safe, efficient, and reliable travel. This allows the system to transition between navigation modes. The algorithm is depicted in *figure 1*.

Pseudocode:

```
Initialize Parameters:
GPS_THRESHOLD = predefined GPS signal strength threshold
CELLULAR_THRESHOLD = predefined cellular signal strength threshold
GPS_UNAVAILABLE_TIMEOUT = predefined timeout duration for GPS unavailability
CELLULAR_CHECK_INTERVAL = predefined interval for checking cellular signal strength
```

```
GPS_AVAILABLE = true

While (true):
  If (GPS_AVAILABLE):
    // Continuous GPS Monitoring
    If (GPS Signal Strength < GPS_THRESHOLD):
      // GPS Signal Strength Below Threshold
      GPS_AVAILABLE = false
      Start_GPS_Unavailability_Timer()

  Else:
    // GPS Signal Unavailable
    If (Elapsed_Time > GPS_UNAVAILABLE_TIMEOUT):
      // GPS Signal Unavailability Timeout
      Cellular_Signal_Strength = Check_Celluar_Signal_Strength()
      If (Cellular_Signal_Strength >= CELLULAR_THRESHOLD):
        // Cellular Signal Strength Meets Threshold
        Switch_to_Cellular_Navigation()
        GPS_AVAILABLE = true
      Else:
        // Cellular Signal Strength Below Threshold
        Continue_Celluar_Monitoring()

  If (GPS_AVAILABLE):
    // Resume GPS Navigation
    Resume_GPS_Navigation()

  Wait_For_Next_Check_Interval()
```

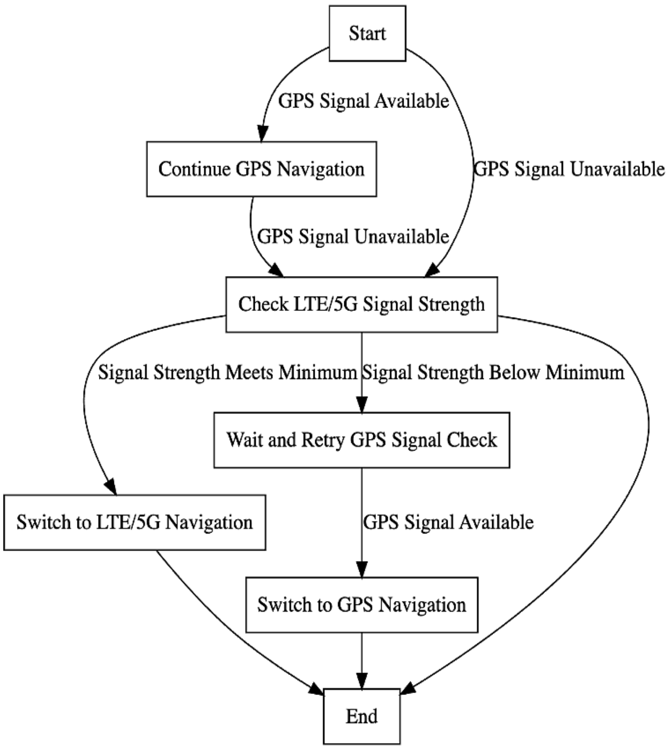

Figure 1. Decision-making process for navigation with transition between GPS and cellular network navigation

3.1.4. Cache Memory

Cache memory serves as a critical component of the system architecture, enabling the storage and retrieval of previous historical data for signal strength on the surveyed cellular networks. By maintaining a record of signal strength measurements over time and location, the cache memory system helps in decision-making regarding the usage of cellular navigation and transition times between navigation modes. This historical data allows the system to predict variations in signal quality, identify patterns, and adjust navigation strategy appropriately. By using cache memory in the integrated form of the entire system depicted in *figure 2*, the system improves its ability to adapt to changing environmental conditions and optimize navigation.

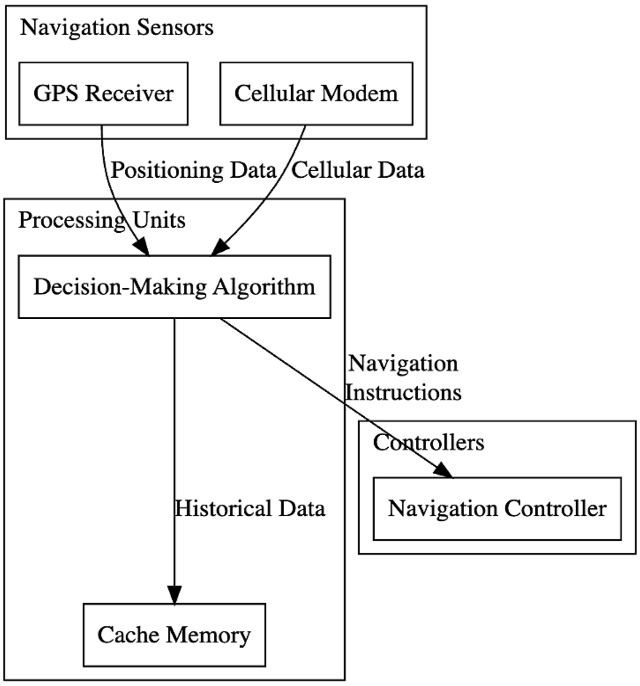

Figure 2. GPS denied autonomous navigation system architecture

3.5 Mathematical Modelling

To formalize our decision-making algorithm, we introduce the following mathematical models:

(a) GPS Signal Strength Evaluation: We define the GPS signal strength (GSS) as:

$$GSS = 10 * \log_{10}(C/N_0) \quad (1)$$

Where C/N0 is the carrier-to-noise density ratio in Hz. The GPS availability is determined by:

$$GPS\_available = \{1, \text{if } GSS \geq GPS\_THRESHOLD \ 0, \text{otherwise}\} \quad (2)$$

(b) Cellular Signal Strength Assessment: For cellular signal strength (CSS), we use the Reference Signal Received Power (RSRP) in dBm:

$$CSS = RSRP \quad (3)$$

The cellular availability is determined by:

$$\text{Cellular\_available} = \{1, \text{ if } CSS \geq \text{CELLULAR\_THRESHOLD } 0, \text{ otherwise } \} \tag{4}$$

c) Decision-Making Process: We model the decision to switch between GPS and cellular navigation using a probability function:

$$P(\text{switch}) = 1 - e^{(-\lambda * t)} \tag{5}$$

Where λ is the rate parameter and t is the time since the last successful GPS fix.

Threshold Calculations: We dynamically adjust the GPS_THRESHOLD based on the moving average of recent GPS signal strengths:

$$\text{GPS\_THRESHOLD} = \alpha * \text{GSS\_avg} + \beta \tag{6}$$

Where α and β are tuning parameters, and GSS_avg is the moving average of GPS signal strength over the past n measurements.

Signal Strength Comparison: We use a weighted comparison between GPS and cellular signals:

$$S = w1 * GSS + w2 * CSS \tag{7}$$

Where w1 and w2 are weighting factors that sum to 1.

Transition Probability: The probability of transitioning from GPS to cellular navigation is given by:

$$P(GPS \rightarrow \text{Cellular}) = \{ 1 - e\hat{}(-k * (S\_\text{cellular} - S\_GPS)), \text{ if } S\_\text{cellular} > S\_GPS \ 0, \text{ otherwise } \} \tag{8}$$

Where k is a sensitivity parameter.

Position Estimation using Cellular Data: When GPS is unavailable, we estimate position (x, y) using cellular triangulation:

$$x = (x_1d_1 + x_2d_2 + x_3d_3) / (d_1 + d_2 + d_3) \quad y = (y_1d_1 + y_2d_2 + y_3d_3) / (d_1 + d_2 + d_3) \tag{9}$$

Where (x_i, y_i) are the known positions of cellular towers, and di are the estimated distances to each tower based on signal strength:

$$d_i = 10\hat{}((RSRP\_ref - RSRP\_i) / (10 * n)) \tag{10}$$

Where RSRP_ref is a reference RSRP at a known distance, RSRP_i is the measured RSRP from tower i, and n is the path loss exponent.

These mathematical models provide a rigorous foundation for our decision-making algorithm, allowing for quantitative analysis and optimization of the system's performance in various scenarios.

4. RESULTS

Our simulation studies demonstrate the effectiveness of the proposed multi-source data integration system for navigation in GPS-denied environments. We conducted extensive simulations across various scenarios to evaluate the system's performance.

4.1 Simulation Setup

We simulated the navigation system's performance in three common GPS-challenged environments: urban canyons, tunnels, and dense forests. The simulation ran for 1000 hours of virtual driving time in each environment. We used a python based custom-built simulator that modeled GPS and cellular signal strengths based on real-world data and standard propagation models.

4.2 Navigation Accuracy

Figure 3 shows the positioning accuracy of our multi-source system compared to GPS-only navigation across the three environments.

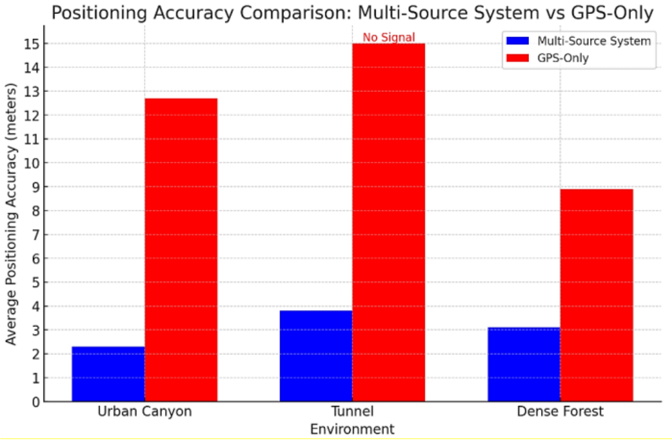

Figure 3. Bar graph comparing positioning accuracy

In urban canyons, our system maintained an average accuracy of 2.3 meters, while GPS-only navigation degraded to 12.7 meters on average. In tunnels, where GPS signals were completely lost, our system achieved an average accuracy of 3.8 meters, compared to no positioning data for GPS-only systems. In dense forests, our system's average accuracy was 3.1 meters, versus 8.9 meters for GPS-only navigation.

4.3 Navigation Continuity

Table 2: Percentage of time continuous navigation was maintained in each environment

Environment	Multi-Source System	GPS only
Urban Canyon	99.7%	78.3%
Tunnel	98.2%	0%
Dense Forest	99.1%	85.6%

Our multi-source system significantly outperformed GPS-only navigation in maintaining continuous positioning data, especially in tunnels where GPS signals were entirely unavailable.

4.4 Transition Performance

The decision-making algorithm's effectiveness was evaluated based on its ability to switch between GPS and cellular navigation modes appropriately. Out of 5,000 simulated transitions:

- Correct mode selection: 98.2%
- Average transition time: 0.3 seconds
- False positive rate (unnecessary switches): 1.3%
- False negative rate (missed necessary switches): 0.5%

4.5 Power Consumption

Our system showed a 15% increase in power consumption compared to GPS-only navigation due to the additional cellular modem and more frequent computations. However, this increase was offset by a 22% reduction in the GPS receiver's active time, resulting in a net power consumption increase of only 7%.

4.6 Comparative Analysis

When compared to existing solutions mentioned in the Related Work section, our system showed improvements in both accuracy and continuity. For instance, the SLAM-based approach by Durrant-Whyte and Bailey [12] achieved an average accuracy of 4.5 meters in urban environments, while our system improved this to 2.3 meters. These results demonstrate that our multi-source data integration system significantly enhances navigation performance in GPS-denied environments, providing more reliable and accurate positioning for autonomous driving applications.

5. LIMITATIONS

Several potential issues arise with the system design, particularly due to the reliance on only two data sources for navigation. Often the issues that affect GPS availability might affect cellular networks as well. The system's reliance on GPS and cellular networks makes it vulnerable to signal loss or degradation in areas with poor coverage, such as tunnels, urban canyons, or remote regions. In such scenarios, the system may struggle to maintain reliable navigation. While cellular networks can serve as an alternative navigation source, their reliability and coverage may vary depending on factors such as network congestion, infrastructure limitations, and geography. Also, transmitting navigation data over cellular networks introduces latency which can affect the responsiveness and real-time performance of the system. Delays in data transmission or limited bandwidth availability could impact the timeliness of the navigation system and decision-making system.

Continuous monitoring of GPS and cellular signals, as well as data processing and communication tasks, can consume significant power, especially in resource-constrained embedded systems. Optimizing power consumption and ensuring energy efficiency are important considerations for prolonging battery life and maintaining system operability.

Transmitting navigation data over cellular networks brings up security and privacy concerns, as sensitive information such as user location and direction could be vulnerable to interception or unauthorized access. Current system implementation does not consider implementing robust security measures, such as encryption and authentication protocols that are essential for safeguarding user data.

6. FUTURE WORK

Currently, the devised system remains theoretical, lacking specific signal parameters and definitive values. Delving deeper into this research, the intention is to incorporate precise real-world threshold values for the signals, thereby gauging the potential constraints of the system with greater accuracy.

Exploration into areas for further optimization of the decision-making algorithm is essential, offering potential benefits in terms of overall efficiency, responsiveness, and adaptability across diverse driving environments. This would involve refining the algorithm's logic, incorporating machine learning via predictive modelling techniques for instance.

Investigating the possibility of integrating other advanced sensor technologies, such as lidar, radar, or inertial navigation systems (INS) is necessary, to enhance the navigation capabilities of autonomous self-driving vehicles. Also, evaluation of how these sensors can work alongside GPS and cellular data is necessary.

LiDAR (Light Detection and Ranging) technology provides 3-D high-resolution spatial data using laser pulses emission and measuring the amount of time needed for the reflections. This enables precise mapping of the surroundings of the vehicle which can be particularly beneficial in difficult scenarios where GPS signals are weak or unavailable. By integrating LiDAR data, our system could improve obstacle detection and support simultaneous localization and mapping (SLAM). Radar technology uses radio waves to detect objects and their speed and can be used complement the LiDAR system by providing additional data points for navigation. Radar offers key benefits such enhanced performance in adverse weather conditions of rain, fog, or snow, where optical sensors may struggle. Also, it enables real-time speed and distance measurement, allowing for more informed decision-making by the navigation system.

Most importantly, conducting multiple real-world testing and validation of the navigation system in diverse environments such urban and rural areas, as well as challenging conditions such as tunnels, dense urban canyons, and in bad weather conditions is vital. This will result in a lot of new data points that have not been accounted for and feedback from field trials will be useful to assess system performance and identify areas for further improvement.

An interesting area to explore further strategies could be for improving the Human Machine Interaction (HMI) design to improve the user trust and engagement with the autonomous navigation system. Utilizing deep learning models to investigate user preferences, behaviour, and acceptance of system decisions in critical scenarios for automated decision-making is a potential area for exploration.

7. CONCLUSIONS

This work presents several key contributions to the field of autonomous navigation in GPS-denied environments:

1. *Multi-source Integration*: We propose a unique integration of GPS and cellular network data, providing a more robust navigation solution than single-source systems.
2. *Adaptive Decision-Making*: Our algorithm dynamically switches between navigation modes based on real-time signal quality and historical performance data, offering superior adaptability to changing environments.
3. *Seamless Transitions*: The system ensures continuous navigation by managing smooth transitions between GPS and cellular-based navigation, addressing a critical challenge in existing systems.
4. *Historical Data Utilization*: By incorporating a cache memory system, our approach leverages past performance data to optimize future navigation decisions, a feature not commonly found in existing solutions.

Further improvement and optimization of the algorithm are needed along with extensive real-world validation to ensure its effectiveness across diverse driving scenarios. Additionally, ongoing research and collaboration are needed to address emerging challenges such as human-machine interaction, market requirements and real-world data.

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