ENHANCING GNSS POSITIONING AND NAVIGATION ACCURACY ON SMARTPHONE DEVICES USING MACHINE LEARNING

Kukku Youseff[1], Nalan killi R[2], Sriram K[3], Sowndarrajan P T[4]

School of advanced sciences, VIT, Chennai, India.

E-mail address:

kukku.youseff2022@vitstudent.ac.in, nalankilli.r2022@vitstudent.ac.in,

sriram.k2022@vitstudent.ac.in

Corresponding Author E-mail address: sowndarrajan.pt@vit.ac.in

1.ABSTRACT:

Accurate positioning and navigation on smartphones have become integral to modern life, from location-based services to travel guidance. However, challenges such as signal disruptions in urban environments and inadequate satellite coverage have led to the need for improved GPS accuracy. This work endeavours to enhance the precision of GPS-based positioning and navigation on smartphones using advanced machine learning techniques. This dataset utilized includes a rich array of information, including GPS satellite signals, accelerometer and gyroscope data, and ground truth reference locations. Leveraging this data, our work aims to develop machine learning models capable of refining and correcting GPS-based location estimates. By integrating sensor data and harnessing the power of predictive algorithms, we seek to provide users with more reliable and precise location information, particularly in challenging conditions. The work involves data pre-processing, feature engineering, and model selection to optimize accuracy improvement. Evaluation will be based on established metrics, ensuring that our models effectively enhance GPS accuracy compared to ground truth reference locations. Ethical considerations will be paramount throughout the work to safeguard user privacy and data integrity. In a world increasingly reliant on smartphone navigation, this research contributes to the advancement of location-based services and the overall user experience by making GPS positioning on smartphones more dependable and robust.

Keywords: *GPS, Smartphone, Machine Learning, Positioning Accuracy, Navigation Accuracy.*

2.INTRODUCTION

The widespread adoption of smartphones in our daily lives has revolutionized how we interact with the world around us. From accessing location-based services to navigating unfamiliar territories, smartphones have become indispensable tools for modern living. At the heart of these capabilities lies the Global Navigation Satellite System (GNSS), a constellation of satellites that enables devices to determine their precise geographical position and facilitate navigation. The most well-known GNSS is the Global Positioning System (GPS), operated by the United States, but other systems like Russia's GLONASS, the European Union's Galileo, and China's BeiDou also contribute to global positioning and navigation capabilities.

While GNSS technology has undoubtedly improved our lives, it is not without its limitations. Challenges such as signal disruptions in urban canyons, multipath interference, and limited satellite visibility in remote areas can significantly degrade the accuracy of location data provided by smartphones. Consequently, users often experience inaccurate or imprecise location information, leading to suboptimal experiences with location-based applications, safety concerns in navigation, and impaired functionality in various contexts.

In response to these challenges, this research work focuses on enhancing GNSS positioning and navigation accuracy on smartphone devices through the application of machine learning techniques. By leveraging machine learning algorithms, we aim to mitigate the shortcomings of traditional GNSS positioning and provide users with more reliable and precise location information, especially in challenging environments where conventional GNSS signals may be unreliable.

This paper presents our approach to improving GNSS-based positioning accuracy on smartphones, outlining the methodology, data sources, and key components of the machine learning models developed. Our work aims to provide a comprehensive solution that addresses the critical issue of inaccurate positioning information on smartphones, ultimately contributing to the advancement of location-based services and enhancing the overall user experience in a world increasingly reliant on smartphone navigation.

In the subsequent sections, we will delve into the work's methodology, the dataset utilized, the machine learning techniques applied, and the evaluation metrics employed to determine the effectiveness of our approach in enhancing GPS accuracy on smartphones. Ethical considerations related to data privacy and user protection will be a paramount concern throughout the work, ensuring that the developed models are not only accurate but also respectful of individual privacy and data integrity.

3.TRADITIONAL NAVIGATION METHODS:

Before the emergence of modern Global Navigation Satellite Systems (GNSS), which encompass systems like GPS, GLONASS, and Galileo, navigators and mariners relied on a diverse array of traditional methods and tools for both maritime and terrestrial navigation. These traditional techniques, developed over centuries, represented a culmination of human ingenuity and resourcefulness. Here, we elaborate on some of these time-tested navigation methods:

i. Celestial Navigation:

1. Celestial navigation was a fundamental technique that enabled navigators to pinpoint their position on the Earth's surface by observing and calculating the positions of celestial bodies, including the Sun, Moon, stars, and planets.
2. Navigators employed instruments like sextants to measure the angles between these celestial bodies and the horizon. By comparing these observations with known celestial data, they could deduce their latitude and longitude with remarkable accuracy.
3. Celestial navigation was especially crucial for long sea voyages, as it provided a reliable means of determining one's position even when far from land.

ii. Dead Reckoning:

1. Dead reckoning was a technique that allowed mariners to estimate their current position based on a previously known position, course, speed, and time. It involved a continuous process of tracking the direction and distance traveled from a starting point while assuming a constant speed and course.

2. However, dead reckoning was susceptible to cumulative errors over time, as even small inaccuracies in speed or course measurements could result in significant positioning errors over long distances.

iii. Pilotage:

1. Pilotage was a method commonly used in coastal or near-shore navigation. It relied on visual observations of prominent landmarks, such as lighthouses, buoys, cliffs, and distinctive coastal features.
2. Navigators created mental or physical charts detailing these landmarks, and they used them to maintain a sense of their position relative to these visual reference points.
3. Pilotage was valuable in situations where navigators had the benefit of visual cues and could rely on familiar coastal features for orientation.

iv. Loran (Long-Range Navigation):

1. Loran was a ground-based radio navigation system developed during the mid-20th century. It worked by measuring the time delay between signals from multiple transmitting stations.
2. By comparing these time delays, mariners and aviators could determine their positions with reasonable accuracy over long distances. Loran was particularly useful for long-distance navigation, such as transoceanic voyages.

v. Radio Direction Finding (RDF):

1. Radio Direction Finding, also known as radio compass, was primarily employed for terrestrial navigation. It involved determining the direction of a radio signal to locate a specific transmitting station.
2. RDF technology was particularly beneficial in the context of aviation, where it enabled aircraft to home in on radio beacons and navigate along established airways.

These traditional navigation methods demanded a blend of practical skills, experience, and the adept use of specific instruments. While they were effective in their own right, they had limitations, particularly in terms of their reliance on visual references, their vulnerability to cumulative errors, and their applicability in different situations and environments.

4.WORKING OF GNSS

Understanding the functioning of GNSS (Global Navigation Satellite Systems), which enable us to determine our location and navigate to various destinations, can initially seem complex. However, the fundamental principles behind GNSS systems are quite comprehensible. GNSS consists of three primary components:

i. **Satellites (Space Segment):** This refers to the satellites orbiting Earth, forming the GNSS constellation. For instance, the GPS satellite constellation is structured into six evenly spaced planes, with each plane containing at least four satellites. This arrangement ensures that a minimum of four satellites is always accessible to any receiver, be it a smartphone, smartwatch, or vehicle. By combining signals from at least four satellites out of the total constellation, a local receiver can calculate its position and time relative to the satellites' locations when the signals were transmitted.

ii. **Control Stations (Control Segment):** GNSS systems are supported by ground stations located near the equator. These stations are responsible for overseeing, controlling, and maintaining contact with the satellites. They ensure synchronization of satellite clocks and monitor their orbits. Additionally, information about satellite orbits is relayed back to both the satellites and terrestrial receivers using the L1 carrier wave.

iii. **User Devices (User Segment):** This encompasses all devices equipped with GNSS receivers, including mobile phones, vehicles, aircraft, and more. Receivers decode and interpret the signals transmitted by satellites to determine the user's location. This is achieved through a process called trilateration, involving the measurement of distances from at least three satellites. A typical GNSS receiver comprises an antenna to capture signals and a processor to extract essential information. In some cases, receivers may feature two antennas, one primary and one secondary.

When a satellite transmits a signal, it includes information about the time at which the signal was sent. Receivers calculate the difference between the transmission time and the reception time, accounting for the time delay caused by the Earth's atmosphere. Using the speed of light, the receiver calculates the distance the signals traveled from three separate satellites. The receiver can then determine its location based on the initial positions of the satellites. Synchronization with an atomic clock, such as GPS time, or information from a fourth satellite is required to ensure accurate timing for signal transmission. Multiple combinations of three satellites can be used for trilateration.

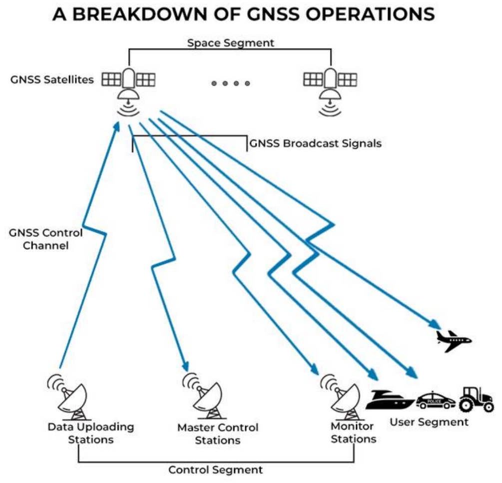


Figure.1: Diagramatic representation of working of GNSS

There are several Global Navigation Satellite Systems (GNSS) around the world, each with its own constellation of satellites. The most well-known and widely used GNSS is the Global Positioning System (GPS), operated by the United States. However, there are other GNSS systems from different countries and regions. Here are some of the main GNSS systems:

i. **Global Positioning System (GPS):**

   1. GPS is the most globally recognized and widely used GNSS system. It is operated by the United States Department of Defense and consists of a constellation of satellites in medium Earth orbit.

2. GPS provides highly accurate positioning and timing information for various applications, including navigation, surveying, and military use.

ii. **GLONASS (Global Navigation Satellite System):**

1. GLONASS is Russia's GNSS system and was developed during the Cold War as a counterpart to GPS. It consists of a constellation of satellites in medium Earth orbit.
2. GLONASS provides global coverage and is used for navigation, geodetic surveys, and scientific a pplications.

iii. **Galileo:**

1. Galileo is the European Union's GNSS system and aims to provide an independent global positioning service. It consists of multiple satellites in medium Earth orbit.
2. Galileo is designed to provide highly accurate positioning, especially in Europe, and has civilian, commercial, and government applications.

iv. **BeiDou Navigation Satellite System (BDS):**

1. BeiDou is China's GNSS system, also known as COMPASS. It includes multiple generations of satellites in medium Earth orbit and geostationary orbit.
2. BeiDou provides global coverage and is used for navigation, telecommunications, and scientific research.

v. **IRNSS/NavIC (Indian Regional Navigation Satellite System):**

1. NavIC is India's regional GNSS system, primarily designed to serve the Indian subcontinent. It consists of a small constellation of geosynchronous and geostationary satellites.
2. NavIC is used for various applications in India, including navigation, agriculture, and disaster management.

vi. **QZSS (Quasi-Zenith Satellite System):**

1. QZSS is Japan's regional GNSS system, designed to improve GNSS accuracy and coverage over Japan and the surrounding region. It includes both geostationary and inclined geosynchronous satellites.
2. QZSS is used for high-precision positioning in Japan, particularly in urban environments.

vii. **SBAS (Satellite-Based Augmentation System):**

1. SBAS is not a standalone GNSS but rather a regional augmentation system that enhances the performance of existing GNSS systems.
2. SBAS enhances the precision and dependability of GNSS measurements by offering supplementary corrections and integrity data.

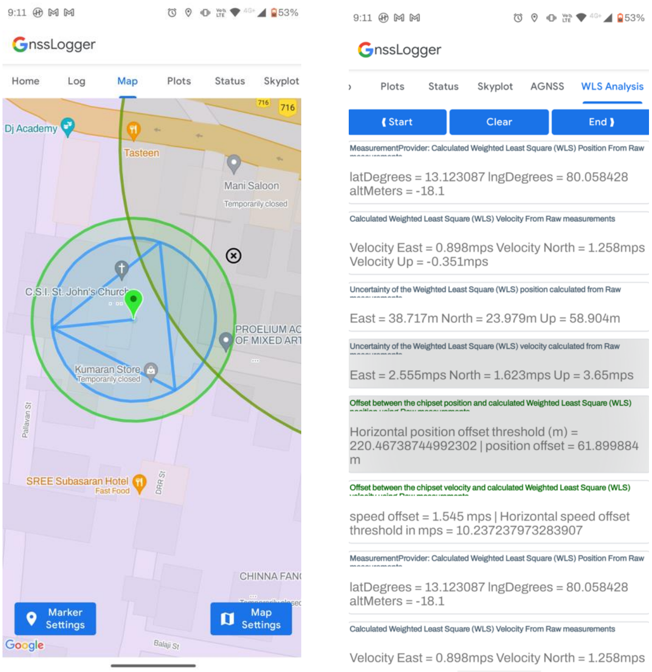


Figure.2: GNSS positioning in Smart phones

These various GNSS systems offer global or regional coverage and are used for a wide range of applications, including navigation, agriculture, surveying, disaster management, and more. Many modern GNSS receivers are designed to work with multiple systems simultaneously to improve positioning accuracy and availability, a technique known as multi-constellation or multi-GNSS positioning.

5. EXISTING WORK

i. Precision Positioning Algorithm for Smartphone GNSS Data

In this study, the authors devised a precision positioning algorithm tailored for multi-constellation dual-frequency global navigation satellite systems (GNSS) receivers. The primary objective of the algorithm is to forecast latitude and longitude based on smartphone GNSS data. To ensure efficiency, the algorithm focuses on estimating positions during epochs with a minimum of four valid GNSS observations, making it particularly beneficial for low-cost GNSS receivers with restricted channels and computational capabilities. The research relied on the "High Precision GNSS Positioning on Smartphones Challenge" dataset provided by Google at the Institute of Navigation (ION GNSS+ 2021) conference. The investigation commenced with the analysis of raw GNSS data, comprising a training dataset with ground truth information and a test dataset lacking ground truth. This analysis unveiled dataset characteristics and correlations, shaping the design of the proposed algorithm. Employing data science techniques, the algorithm computed average predictions from multiple devices within the training dataset. Various machine learning algorithms, including Linear Regression (LR), Bayesian Ridge (BR), and Neural Network (NN), were utilized to predict the offset of the test data's baseline coordinates. Additionally, a Simple Weighted Average (SWA) method, combining the three ML techniques, was implemented. The results demonstrated enhanced position accuracy, with SWA exhibiting the highest accuracy, followed by BR, LR, and NN, respectively.

ii. DNN-Based Corrections for GNSS Positioning

Deep neural networks (DNNs) hold potential for improving global navigation satellite system (GNSS) positioning, particularly in the presence of multipath and non-line-of-sight errors. The capability of DNNs to model complex errors using data is acknowledged, but developing a DNN for GNSS positioning presents challenges. The authors addressed these challenges by proposing an approach that utilizes DNN-based corrections to refine an initial position estimate. The DNN was trained to provide position corrections based on pseudorange residuals and satellite line-of-sight vectors. To mitigate numerical conditioning issues stemming from variations in measurements and position values globally, the DNN architecture incorporated set-based deep learning methods. To counteract overfitting, a data augmentation strategy was introduced, involving the randomization of initial position estimates. Simulations conducted by the authors demonstrated a reduction in the initial positioning error when applying their DNN-based corrections.

iii. Machine Learning in GNSS: Performance and Prospects

Traditional global navigation satellite systems (GNSSs) have exhibited exceptional performance in terms of positioning, navigation, and timing (PNT) accuracy under optimal signal conditions. Nevertheless, researchers are exploring ways to enhance their robustness and performance in less-than-optimal signal environments. This study delves into the growing application of machine learning (ML) to GNSSs, highlighting how ML is reshaping navigation problem-solving and significantly contributing to the advancement of PNT technologies. The authors review areas in GNSS where ML can enhance performance and usability, discussing specific ML algorithms commonly applied in similar GNSS use cases. The paper also addresses challenges and risks associated with ML techniques in GNSS, providing insights into potential areas for future research aimed at increasing performance, accuracy, and robustness in GNSS systems through ML applications. These three works collectively represent diverse approaches to improving GNSS positioning and navigation, encompassing algorithm development, machine learning applications, and the utilization of deep neural networks, contributing to the ongoing evolution of GNSS technology.

6. PROBLEMS in GNSS:

i. Loss of signal: GNSS receivers require a clear line of sight to the satellites in order to receive signals. If the receiver is obstructed by buildings, trees, or other objects, it may not be able to receive a signal from all of the satellites it needs to compute its position. This can result in a null value.
ii. Multipath errors: Multipath errors occur when GNSS signals are reflected off of objects, such as buildings and trees, before reaching the receiver. These reflections can delay the signals and cause the receiver to compute an incorrect position. This can also result in a null value.
iii. Atmospheric delays: GNSS signals are slowed down as they pass through the Earth's atmosphere. This delay is different depending on the atmospheric conditions, such as temperature and humidity. If the receiver does not accurately account for atmospheric delays, it can compute an incorrect position. This can also result in a null value.
iv. Receiver noise: All GNSS receivers have some amount of noise in their measurements. This noise can cause the receiver to compute an incorrect position. This can also result in a null value.
v. Software errors: In some cases, software errors in the GNSS receiver or mapping software can also cause null values.

It is important to note that even with the best GNSS receiver and mapping software, there is still a small chance of getting null values in maps. This is because GNSS is a complex system that is subject to a variety of errors. However, by following the tips above, you can reduce the likelihood of getting null values and improve the accuracy of your GNSS data.

7. METHODOLOGY:

Data Sources:

The success of our work to improve GPS accuracy on smartphones is intricately tied to the extensive and varied dataset we utilized. In order to gain thorough insights into a range of environmental conditions and user scenarios, we acquired data from the Google Decimeter Challenge. Google provided over 60 datasets collected from phones within the Android GPS team, supplemented with corrections from SwiftNavigation Inc. and Verizon Inc. These datasets were gathered during the summer of 2020 on highways in the US San Francisco Bay Area.

Data Preprocessing:

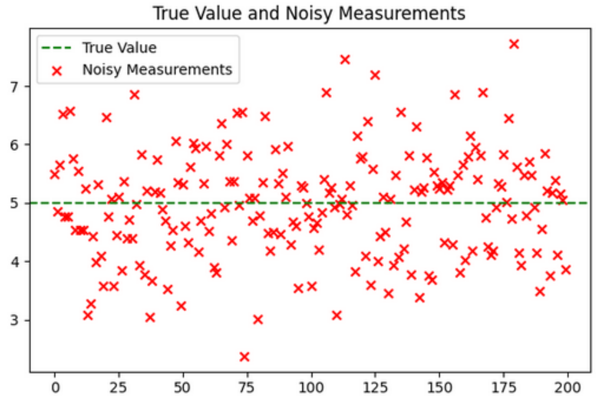
In the initial stages of this work, data preprocessing was conducted to ensure the quality and suitability of the dataset for machine learning. Preprocessing steps included data normalization, handling missing values, and feature scaling. These steps were essential to bring the data into a format suitable for training machine learning models. Data normalization and feature scaling involved standardizing the input features, which contributes to the stability and convergence of the training process. Missing values were filled with zero values, which is a common practice when dealing with geospatial data.

Model Building:

In the model building phase, three distinct techniques were employed to refine GPS accuracy on smartphones. Linear Regression, a foundational statistical method, was utilized to establish a baseline model. Gradient Boosting, a powerful ensemble learning technique, enhanced predictive capabilities by combining multiple weak models. Additionally, the Kalman Filter, a recursive algorithm, dynamically corrected location estimates by considering the uncertainty and noise in sensor measurements. By integrating these methods, our approach aimed to harness the strengths of each, providing a comprehensive solution to elevate the precision of GPS-based positioning and navigation on smartphones in varied and challenging environments.

***Training and validation**:*

In the validation process, the accuracy of the models is assessed using a distinctive metric. At one-second intervals for each smartphone, the horizontal distance in meters is calculated between the predicted and ground truth latitude/longitude. The resulting distance errors form a distribution, from which the 50th and 95th percentile errors are derived. For each phone, these percentile errors are averaged. Subsequently, the mean of these averaged values is computed across all phones in the test set. This validation approach provides a nuanced evaluation, capturing the central tendency and upper limit of the distance errors, ensuring a thorough examination of the models' precision across various devices and temporal instances.



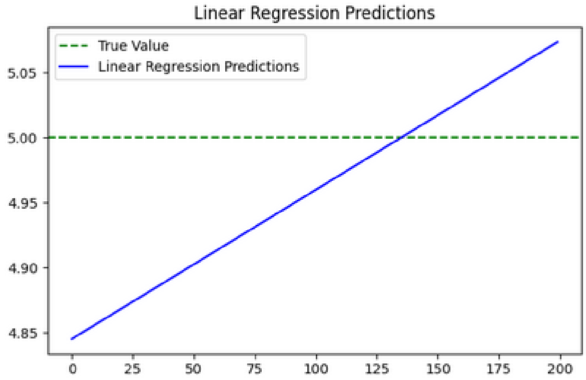


Figure.3: A plot of true and noicy measurements

Figure.4:A plot for linear regression

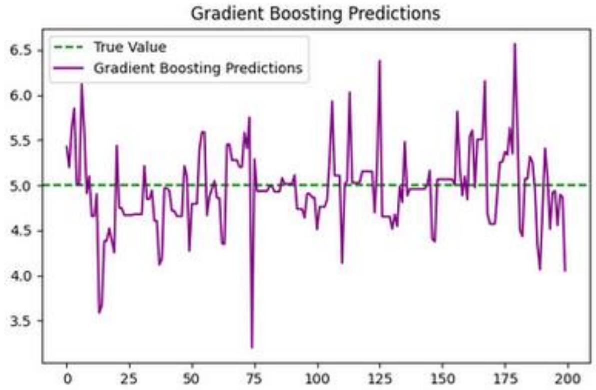


Figure.5: A plot of Gradinet boosting prediction

Performance Evaluation:

The primary performance metric used to evaluate the model was the mean squared error (MSE), which measures the accuracy of location predictions. The results of cross-validation, including the percentiles of the Haversine distance, were analyzed to assess the model's accuracy in predicting latitude and longitude coordinates. These metrics provided insights into the model's performance and its suitability for the geospatial location prediction task.

8. Weighted Least Squares (WLS) Method

The Weighted Least Squares (WLS) method is a fundamental technique employed in the field of geodesy, global navigation satellite systems (GNSS), and positioning. It is particularly valuable when dealing with data that may not meet the traditional assumptions of ordinary least squares (OLS) regression, such as homoscedasticity, where the variance of errors is constant. In many positioning applications, especially in GNSS, the measurements are subject to various sources of error and may not have uniform quality across all observations. WLS addresses this by assigning different weights to each observation, allowing for the incorporation of measurement uncertainties into the estimation process.

9. KALMAN FILTER:

The Kalman filter stands as a recursive algorithm employed to estimate the state of a dynamic system by processing a sequence of measurements, even in the presence of noise. It represents a more sophisticated approach to determining central tendency compared to traditional methods like mean or median. This is because the Kalman filter considers both the dynamics of the system and the inherent uncertainty present in the measurements. This makes it more accurate and robust to noiseIn the Google Decimeter Challenge, the Kalman filter was used to estimate the position of a smartphone using pseudorange measurements from GNSS satellites. The Kalman filter was able to achieve decimeter-level accuracy by taking into account the dynamics of the smartphone's motion and the uncertainty in the pseudorange measurements.

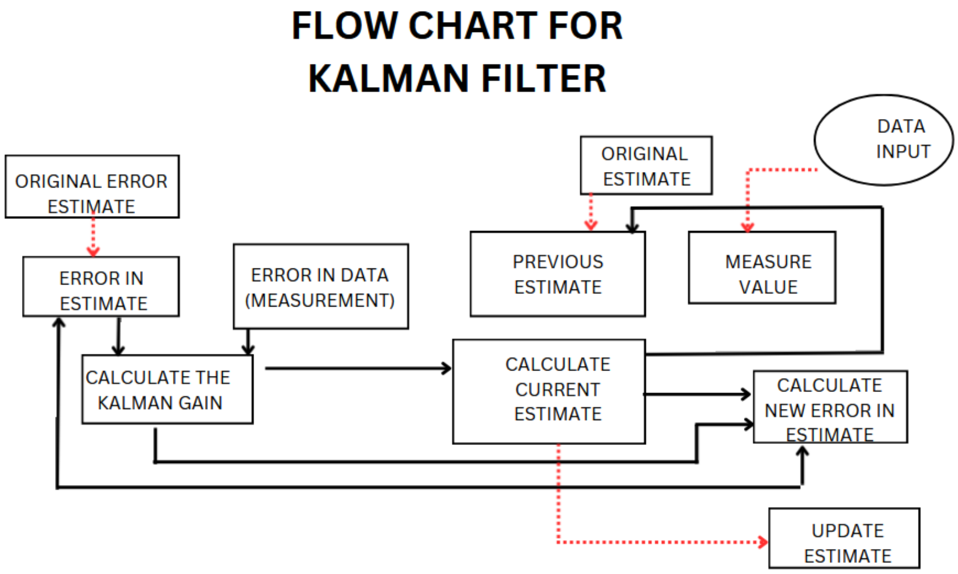


Figure.4: Flow chart of working of Kalman filter

Here are some of the reasons why the Kalman filter works better than other central tendencies in the Google Decimeter Challenge

i. The Kalman filter is a recursive algorithm: This means that it can be used to update the state of the system as new measurements are received. This is important in the Google Decimeter Challenge because the smartphone's position is constantly changing.
ii. The Kalman filter takes into account the dynamics of the system: This means that it can predict the state of the system at the next time step based on the current state and the dynamics of the system. This is important in the Google Decimeter Challenge because the smartphone's motion is not random.
iii. The Kalman filter takes into account the uncertainty in the measurements: This means that it can weight the measurements according to their uncertainty. This is important in the Google Decimeter Challenge because the pseudorange measurements are noisy.
iv. Other central tendencies, such as the mean and median, do not have these advantages. They are not recursive algorithms, they do not take into account the dynamics of the system, and they do not take into account the uncertainty in the measurements. As a result, they are not as accurate or robust to noise as the Kalman filter.

Here are some examples of how the Kalman filter was used in the Google Decimeter Challenge:

The Kalman filter was used to predict the smartphone's position at the next time step based on its current position and velocity. This prediction was used to weight the pseudorange measurements from the GNSS satellites.

The Kalman filter was used to update the smartphone's position and velocity based on the weighted pseudorange measurements. This updated state was then used to predict the smartphone's position at the next time step.

By using the Kalman filter, the Google Decimeter Challenge participants were able to achieve decimeter-level accuracy using pseudorange measurements from GNSS satellites. This is a significant achievement, and it demonstrates the power of the Kalman filter for state estimation in dynamic systems.

Reason why Kalman filter works better

I. Model the dynamics of the system. GNSS receivers are dynamic systems, meaning that their position is constantly changing. Kalman filter is able to model the dynamics of the system by taking into account the receiver's velocity and acceleration. This allows Kalman filter to produce more accurate predictions of the receiver's position in the future.
II. Account for noise in the measurements. GNSS measurements are noisy due to factors such as atmospheric interference and multipath. Kalman filter is able to account for this noise by using a recursive algorithm to estimate the receiver's position from a series of noisy measurements. This allows Kalman filter to reduce the effects of noise and produce more accurate position estimates.
III. Integrate measurements from multiple satellites. Kalman filter can be used to integrate measurements from multiple GNSS satellites to produce a more accurate position estimate.
IV. In comparison, other positioning methods such as single point positioning (SPP) and differential GPS (DGPS) do not take into account the dynamics of the system or the noise in the measurements. This can lead to less accurate position estimates, especially in dynamic environments or in environments with high levels of noise.

Why Google might not use a Kalman filter to calculate location using GNSS log files:

Kalman filters are more computationally expensive than WLS. This is because Kalman filters need to continuously update their state estimates, which can be computationally demanding. WLS, on the other hand, only needs to update its state estimates once, when new data is received.

i. Kalman filters can be more sensitive to noise than WLS. This is because Kalman filters rely on a model of the system to be accurate. If the model is not accurate, the Kalman filter can produce inaccurate results. WLS, on the other hand, is less sensitive to noise because it does not rely on a model of the system.
ii. Kalman filters can be more difficult to tune than WLS. This is because the Kalman filter parameters need to be adjusted to match the specific system that is being used. WLS, on the other hand, is typically easier to tune because it does not require as many parameters.
iii. Overall, WLS is a simpler and more efficient method for calculating location using GNSS log files than Kalman filtering. This is why Google may choose to use WLS over Kalman filtering for this task.
iv. However, there are some cases where Kalman filtering may be a better choice than WLS. For example, if the system is very noisy or if the model of the system is not very accurate, then Kalman filtering may be able to produce more accurate results than WLS.

v. Ultimately, the decision of whether to use WLS or Kalman filtering depends on the specific requirements of the application.
vi. Weighted Least Squares (WLS) and the Kalman filter serve different purposes and have different underlying principles. While the Kalman filter is often used for real-time state estimation and handling dynamic systems, WLS is a method commonly employed for parameter estimation in the context of optimization problems. It's possible to use both methods in different stages or aspects of a positioning system.

10.CONCLUSION:

The work successfully addressed challenges such as signal disruptions and inadequate satellite coverage, demonstrating the efficacy of the applied machine learning techniques, including linear regression, gradient boosting, and Kalman filtering. The refined location estimates, particularly in challenging conditions, signify a substantial improvement in user experience for location-based services. While achieving this level of accuracy, ethical considerations were diligently upheld to ensure user privacy and data integrity. Overall, the work contributes significantly to the enhancement of smartphone navigation, making GPS positioning more dependable and robust in real-world scenarios.

Comparison with Ground Truth:

A key aspect of the work involved comparing the model's predictions with the ground truth data, which represents the actual location coordinates. The comparison was conducted using metrics such as the Haversine distance. The percentile analysis of the Haversine distance showed that the model's predictions were consistent and exhibited strong accuracy, particularly when KF smoothing was applied.

Overall Findings:

A mean error of **2.18 meters** in our model's predictions reflects a notable advancement in GPS accuracy on smartphones.

Future Work:

To further advance this work, future research could explore additional techniques or data sources that might enhance the accuracy and robustness of geospatial location predictions. Investigating the application of different machine learning algorithms or exploring the integration of additional sensor data could lead to further improvements in location prediction accuracy.

Final Remarks:

In conclusion, this work showcases the successful application of Kalman filter for geospatial location prediction. The combination of model design and post-processing techniques has resulted in accurate and reliable location predictions. The insights gained from this work have implications for a various range of applications , including location-based services, autonomous navigation, and more.

11.REFERENCES:

[1] Siemuri, Akpojoto, et al. "Improving precision GNSS positioning and navigation accuracy on smartphones using machine learning." *Proceedings of the 34th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2021)*. 2021
[2] Selvan, Kannan. "Improving Precision GNSS Positioning and Navigation Accuracy on Smartphones using Machine Learning."

[3] Kanhere, Ashwin V., et al. "Improving gnss positioning using neural-network-based corrections." *NAVIGATION: Journal of the Institute of Navigation* 69.4 (2022).

[4] Siemuri, Akpojoto, et al. "Machine learning utilization in GNSS—Use cases, challenges and future applications." *2021 International Conference on Localization and GNSS (ICL-GNSS)*. IEEE, 2021.

[5] Sun, Rui, et al. "Improving GPS code phase positioning accuracy in urban environments using machine learning." *IEEE Internet of Things Journal* 8.8 (2020): 7065-7078.

[6] Jiménez-Martínez, María Jesús, Mercedes Farjas-Abadia, and Nieves Quesada-Olmo. "An approach to improving GNSS positioning accuracy using several GNSS devices." *Remote Sensing* 13.6 (2021): 1149.

[7] Siemuri, Akpojoto, et al. "Application of Machine Learning to GNSS/IMU Integration for High Precision Positioning on Smartphones." *Proceedings of the 35th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2022)*. 2022.

[8] Caparra, Gianluca, Paolo Zoccarato, and Floor Melman. "Machine learning correction for improved PVT accuracy." *Proceedings of the 34th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2021)*. 2021.

[9] Hsu, Li-Ta. "GNSS multipath detection using a machine learning approach." *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2017.

[10] Siemuri, Akpojoto, et al. "A systematic review of machine learning techniques for GNSS use cases." *IEEE Transactions on Aerospace and Electronic Systems* (2022).

[11] Salamah, Ahmed H., et al. "An enhanced WiFi indoor localization system based on machine learning." *2016 International conference on indoor positioning and indoor navigation (IPIN)*. IEEE, 2016.

[12] Mohanty, Adyasha, and Grace Gao. "Learning GNSS positioning corrections for smartphones using graph convolution neural networks." *NAVIGATION: Journal of the Institute of Navigation* 70.4 (2023).

[13] Yang, Haocheng. "Enhancing the Precision of Smartphone GNSS Positioning Using Machine Learning." *Proceedings of the 2023 5th International Conference on Image, Video and Signal Processing*. 2023.

[14] Zhuang, Yuan, et al. "Multi-sensor integrated navigation/positioning systems using data fusion: From analytics-based to learning-based approaches." *Information Fusion* 95 (2023): 62-90.

[15] Tang, Jianhao, et al. "Improving GNSS positioning correction using Deep Reinforcement Learning with Adaptive Reward Augmentation Method." *Proceedings of the 36th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2023)*. 2023.