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Research Article

Secure Autonomous Vehicle Localization Framework using GMCC and FSCH-KMC under GPS-Denied Locations

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Abstract: For safe and efficient navigation, self-driving cars rely on determining their position through a system called Autonomous Vehicle Localization (AVL). Traditional self-driving cars face challenges related to security and speed in finding their location. To address these problems, this article presents a more secure way, called the Secured Localization (SL), to locate the vehicle, even when signals are weak. First, vehicles are registered and logged in. If Global Positioning System (GPS) signals are available, they are processed securely utilizing Gini-Montgomery Curve Cryptography (GMCC); If GPS signals are not available, then the car uses nearby signal points to find its location. SL data and sensed data from the sensors, including Light Detection and Ranging (LIDAR), Radio Detection and Ranging (RADAR), and Camera are given to On Board Unit (OBU). Then, the vehicle's position is matched with a pre-stored map for accurate navigation. Finally, various methods such as Fisher Score Chi-Hell Square based K Means Clustering (FSCH-KMC), Cosine Gramian-Kalman Filter (CG-KF), and Hadoop Distributed File System (HDFS) are applied to prioritize and refine the vehicle's location for better navigation. The proposed framework is simulated and the results show an accuracy of 98%, precision of 98%, and recall of 99%, with improvements in security and faster location finding compared to previous systems.

Keywords: *Cosine Gramian-Kalman Filter (CG-KF); Fisher Score Chi-Hell Square based K Means Clustering (FSCH-KMC); Gini-Montgomery Curve Cryptography (GMCC); Global Positioning System (GPS); Secured Localization (SL)*

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1. Introduction

Secured Localization (SL) is essential for ensuring safe and optimal navigation in the rapidly advancing field of Autonomous Vehicles (AVs). Precise real-time location is critical for AVL, typically obtained via Global Positioning System (GPS) [1]. While GPS is the standard method for determining the position of AVs [2], its signals are often disrupted by obstacles such as buildings, electric clouds, and tunnels, posing significant challenges to autonomous driving [3]. Therefore, ensuring AVL in the absence of GPS signals remains a crucial challenge [4].

To address this, Simultaneous Localization and Mapping (SLAM) techniques have gained prominence in AVL [5]. Moreover, sensor fusion methods, such as RADAR, are employed to detect obstacles in GPS-denied environments [6-7]. While Deep Neural Networks (DNNs) assist with object detection, they are susceptible to noise intrusion [8]. Kalman Filters (KF), including Adaptive KF, are

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commonly used to predict AV positions and movements [9-10]. However, traditional methods face limitations concerning security, accuracy, emergency response speed, and the handling of large-scale data storage and analysis.

To overcome these limitations and ensure safe AV navigation, this research proposes using a Cosine Gramian-Kalman Filter (CG-KF) and Gini-Montgomery Curve Cryptography (GMCC) algorithms for secured localization (SL).

1.1. Problem Statement

Conventional localization techniques in AVL face several challenges, including:

- Managing diverse sensor data, which can lead to data storage and processing errors.
- Lack of security, which creates vulnerabilities in the AV ecosystem.
- Delays in responding to unexpected obstacles, often causing hesitation or abrupt swerving.

The primary objectives of the proposed work are as follows:

- To address big data challenges, the Hadoop Distributed File System (HDFS) is implemented for efficient sensor data storage
- For securing the vehicle's location, a secret key with encryption is deployed using the Gini-Montgomery Curve Cryptography (GMCC) algorithm
- Advanced algorithms such as the Pareto Distribution-based Hidden Markov Model (PD-HMM), Fisher Score Chi-Hell Square-based K-Means Clustering (FSCH-KMC), and Cosine Gramian-Kalman Filter (CG-KF) are employed to enhance precise navigation

The remaining paper has been systematized as: section 2 discusses the related works and their limits, the proposed AVL methodology is displayed in Section 3, outcomes and discussion are exemplified in Section 4, and finally, the paper is wrapped up in Section 5.

2. Literature Survey

Kasmi *et al*. [11] presented an end-to-end Ego-Localization (EL) for ensuring AV safety navigation. For ego-lane determination, OpenStreetMap (OSM) datasets, Bayesian, and Hidden Markov Model (HMM) were utilized by the model. The You Only Look Once (YOLO) detector's purpose outperformed lane-level localization. The overall EL of the system was tackled by the outcomes. Yet, EL accounted for RT road changes, thus limiting its utility.

Steinke *et al*. [12] introduced Geometric Fingerprinting (GF) for precise AVL and mapping utilizing an optional Inertial Measurement Unit. For feature tracking, it utilized LIDAR, and for pole detection, it utilized the Pole Feature Detection Scan Line algorithm. GF was adaptable to several sensors, thus ensuring higher localization accuracy. However, it lacked robustness in bad weather, which affected the accuracy and quality of LIDAR data.

Nguyen *et al*. [13] propounded a Wireless Sensor Network (WSN) for AVL in GPS-denied areas, combining K Nearest Neighbour (KNN) and Support Vector Machine (SVM) methods with Wi-Fi ensemble neural networks and grid-based Markov localization. A stable decrement in global localization error was shown by the result. However, reliance on Wi-Fi could limit reliability in Wi-Fi-deprived GPS-denied areas.

Bersani *et al*. [14] employed an integrated algorithm for efficient Ego-Vehicle (EV) and barrier state estimation in autonomous driving. The KF and Probability Density Function (PDF) were utilized by the algorithm for SL filtering. Obstacles were found and tracked by sensor fusion from the RADAR and LIDAR. The relative position and localization of EVs in AVs were shown by the outcomes. Sensor reliance, which could lead to failures or inaccuracies, was an important drawback.

Lin *et al.* [15] deployed a Planar Primitive group-based Point Cloud Registration Structure for AVL in underground parking lots. For LIDAR 3D data evaluation, the system applied the Iterative Closest Point (ICP), Normal Distribution Transform (NDT) algorithm, and SLAM. The approach determined the parallel efficiency of four datasets to serve RT applications. The model attained decimetre-level localization perfection; however, it has limited applicability in non-planar environments.

The literature review explores various approaches to Autonomous Vehicle Localization (AVL) and their associated challenges. Still, these systems had the following limitations:

- Difficulty to adapt with real-time road changes
- Lacked robustness in poor weather conditions which in turn affects the LIDAR accuracy
- Dependence on Wi-Fi networks and sensors posed potential failure risks
- Accuracy issues in non-planar environments

3. Proposed Methodology for Secured AVL and Navigation

The proposed work employs secured AVL utilizing GMECC and CG-KF-based navigation framework. Figure 1 exemplifies the proposed architecture.

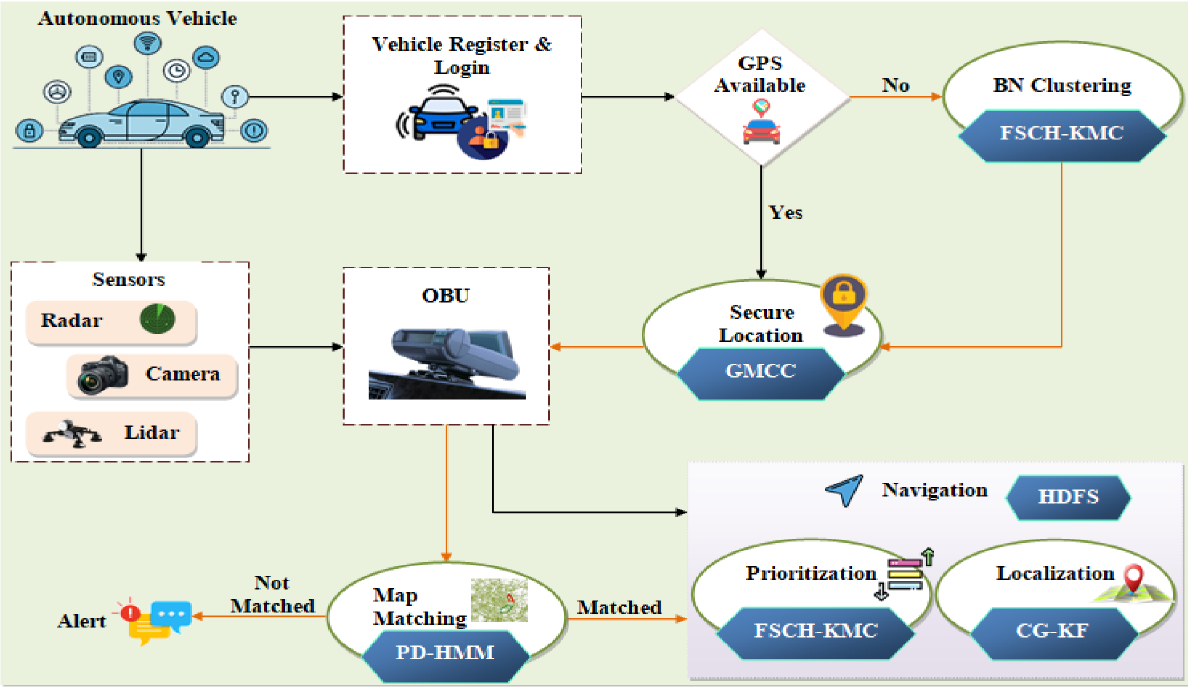


Figure 1. Block diagram of the proposed model

The block diagram in Figure 1 outlines the process of secure localization and navigation in autonomous vehicles (AVs), integrating various technologies and algorithms for accurate vehicle positioning. The workflow begins with the Autonomous Vehicle which registers and logs in through a secure system. The vehicle's sensors—Radar, Camera, and LIDAR—collect data related to the vehicle's surroundings.

Once the vehicle is registered, a decision is made based on GPS availability. If GPS is available, a secure location is determined using the Gini-Montgomery Curve Cryptography (GMCC) algorithm to ensure safe communication and location privacy. In cases where GPS is unavailable, Beacon Node (BN) Clustering is performed using the Fisher Score Chi-Hell Square K-Means Clustering (FSCH-KMC) algorithm for localization without GPS.

The sensor data is processed by the On-Board Unit (OBU), which then sends the data for Map Matching using the Pareto Distribution-based Hidden Markov Model (PD-HMM). If the map matching process identifies discrepancies (i.e., if the data does not match the map), an alert is generated to notify the vehicle of potential issues or inaccuracies.

If the map matching is successful, the system proceeds with Prioritization and Localization. For prioritization, the FSCH-KMC algorithm is employed again to manage and prioritize navigation tasks. For localization, the Cosine Gramian-Kalman Filter (CG-KF) is used to ensure real-time and precise localization. Hadoop Distributed File System (HDFS) is also integrated for managing large sensor datasets, optimizing the navigation process, and ensuring efficient storage of the data.

This integrated system ensures secure, reliable, and precise navigation for autonomous vehicles in various conditions, including GPS-denied environments.

3.1. AV Registration & Login

Primarily, for accessing the vehicle location, vehicle details, namely Identity Document (ID), Source and Destination (SD) messages, GPS ID, and On-Board Unit (OBU) numbers are to be registered and logged in. After that, the GPS availability is checked for routing the AV. If GPS is available, then the number of sensed GPS signals can be articulated as,

$$\delta_k = \delta_1, \delta_2, \dots \dots \delta_n \qquad (k = 1,2, \dots \dots n) \tag{1}$$

3.2. GPS Location Security

Here, δ_k from GPS is encrypted using GMCC for secure navigation. Elliptic Curve Cryptography (ECC) offers faster encryption and decryption as well as enhanced security. However, it faces challenges in generating private keys using random values. The Montgomery curve along with Gini coefficients is employed to address the issue. It provides resistance to quantum attacks and concentrates on point addition and doubling for secure cryptographic calculations. The GMCC algorithm comprises the following steps.

3.2.1. Curve Selection

Firstly, the Gini-based Montgomery curve is selected, and the curve parameters $(\boldsymbol{s_1}, \boldsymbol{s_2})$ including curve equation, coefficients, and base point are described as,

$$s_2 y^2 = 1 - \sum_{s_{i=1}}^{n} x(x^2 + s_i x + 1) \tag{2}$$

Here, $x \ and \ y$ signify the coordinates of curve.

3.2.2. Private and Public Key Computation

Thereafter, from the above curve equation, the private key (d) and base point (b) are generated randomly; then, the public key $(\boldsymbol{Q'})$ is computed through scalar multiplication utilizing adding and doubling methods. Now, two points P and Q are initiated from equation 2. If bit = 1, then two points addition with point (R) takes place.

$$P \oplus Q = R \tag{3}$$

Afterward, the slope μ of the curve is computed by assigning $P = (xP, yP)$, $Q = (xQ, yQ)$ and $R = (xR, yR)$ as,

$$\mu = \left(\frac{yQ - yP}{xQ - xP}\right) \tag{4}$$

$$xR = s_2 * \mu^2 - s_1 - xP - xQ \tag{5}$$

If bit=0, then two points doubling is performed as per the following equations,

$$2P = R \tag{6}$$

$$\mu = \frac{3xP^2 + 2s_1 xP + 1}{2s_2 yP} \tag{7}$$

$$xR = s_2 * \mu^2 - s_1 - 2 * xP \tag{8}$$

$$yR = (2xP + xQ + s_1) * \mu - s_2 * \mu^3 - yP \tag{9}$$

3.2.3. Encryption

Now, the signal (δ_k) is encrypted by utilizing a random integer (v) and $(\boldsymbol{Q'}, \boldsymbol{b})$, which is expressed as,

$$\Psi_1 = (v * b) + S_s \tag{10}$$

$$\Psi_2 = M + \left(v * Q'\right) + S_s \tag{11}$$

Here, Ψ_1, Ψ_2 exemplify the cipher texts created for the input GPS signals.

3.2.2. Decryption

Thereafter, the encrypted data is imported into OBU; it is then decrypted by employing (d). The decrypted signal (M) is formulated as,

$$M = \left((\Psi_2 - d) * \Psi_1\right) - b \tag{12}$$

3.3. BN Clustering

By utilizing the FSCH-KMC technique, the vehicles undergo clustering with pre-initialized BN in GPS-denied areas. FSCH-KMC clustering is chosen as it is more flexible and better at handling non-linear relationships compared to other clustering methods. FSCH-KMC can handle larger datasets more efficiently and provides better handling of overlapping clusters, while hierarchical methods might be more computationally intensive. Also, FSCH-KMC provides more control over cluster membership and can handle cases where clusters are not of uniform density.

KMC has a high convergence ability; yet, the performance is affected by the random centroid initialization. Hence, fisher score-based Chi-hell squared distance is implemented for centroid calculation, which results in efficient clustering outcomes. The steps in FSCH-KMC are described further.

3.3.1. Initialization

Primarily, BN (b_n) is initiated as data points with K −clusters; then, by adopting the Fisher score technique, the centroid is calculated as follows:

$$b_n = \{b_1, b_2, \dots \dots, b_N\} \tag{13}$$

$$\varsigma_i \rightarrow F_s = \frac{\sum_{y=1}^{n} \rho_y (\beta_y - \beta)^2}{\sum_{y=1}^{n} \rho_y \ \sigma_y^2} \tag{1}$$

Here, ς_i implies centroid, F_s elucidates the selected ς_i, β_y signifies data points belonging to a class$y$, σ_y exemplifies standard deviation, and $\rho_y$is the fraction of β_y and β is the global means of data.

3.3.2. Assignment

Chi-hell squared distance $\left(D_{\bar{\chi}^2}\right)$ distances between b_n and F_s is calculated for BN as,

$$D_{\bar{\chi}^2}\left(b_{n_i}, F_{s\,j}\right) = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{N} \frac{\left(b_{n_i} - F_{s\,j}\right)^2}{b_{n_i} + F_{s\,j}}} \tag{2}$$

3.3.3. Updation of Centroid

After $D_{\bar{\chi}^2}$ calculation, F_s for iteration $\tau + 1$, $\left({F_s}^{\tau+1}\right)$ is updated by,

$${F_s}^{\tau+1} = \left(\frac{1}{N_K}\right) * \sum \frac{\left(b_{n_i} - {F_{s\,j}}^{\tau}\right)^2}{b_{n_i} + {F_{s\,j}}^{\tau}} \tag{3}$$

Here, τ implies the iteration number and N_K notates the number of b_n on cluster K.

3.3.4. Convergence Check

Now, the change in F_s $\left(\Delta {F_s}^K\right)$ for all K between the current $\left({F_s}^{\tau+1}\right)$ and previous $({F_s}^{\tau})$ iteration is assessed as,

$$\Delta {F_s}^K = \left\|{F_s}^{\tau+1} - {F_s}^{\tau}\right\| \tag{4}$$

3.3.5. Termination

The above step continues until a maximum number of iterations (τ_{max}) is reached. The Y number of clustered BN (U_k) is determined as,

$$U_k \rightarrow u_1, u_2, \dots \dots u_Y \tag{5}$$

The pseudocode of the proposed FSCH-K Means Clustering is given in Algorithm 1.

Algorithm 1. Pseudocode of the proposed FSCH-K Means Clustering

```
Input: Beacon nodes (b_n)
Output: Clustered BN U_k
Begin
      Initialize beacon nodes
      While τ < τ_max
             Select fisher score centroid F_s
             for 1 < b_n → i < N
                   Compute D_χ̄χ²(b_{n_i}, F_{s j})
                   Evaluate centroid updation F_s^{τ+1}
                   Calculate ΔF_s^K = ||F_s^{τ+1} − F_s^τ||
             End for
      End While
      Obtain U_k → u_1, u_2, ……u_n
End
```

This pseudo-code outlines a clustering algorithm for beacon nodes using Fisher Score-based centroid selection and Chi-square distance. Initially, the beacon nodes are initialized, and the algorithm iterates until a maximum time limit is reached. In each iteration, a centroid is selected based on the Fisher Score, and for each beacon node, the Chi-square distance to the centroid is computed. The centroid is then updated iteratively, and the change in centroid position is calculated. The process continues until convergence or the maximum iterations are met, resulting in clustered beacon nodes as the output.

Thereafter, the clustered BN provides a location for AV. Hence, the location is secured utilizing the GMCC algorithm that is defined above in section 3.2.

3.4. On Board Unit (OBU)

The information on secured location and sensed data from RADAR, LiDAR, and camera are given in OBU. Then, for accurate matching and navigation of AVs, the map obtained from BN clustering and the offline map developed during vehicle initialization are compared utilizing the PD-HMM algorithm.

3.4.1. Map Matching

In this phase, map matching utilizing the PD-HMM algorithm is executed. When contrasted with complicated models, HMM makes better predictions. However, the process of HMM was complicated owing to the large number of states and interactions between them. Hence, the Pareto Distribution is deployed to reduce the interaction between the states. The steps involved in PD-HMM are as follows.

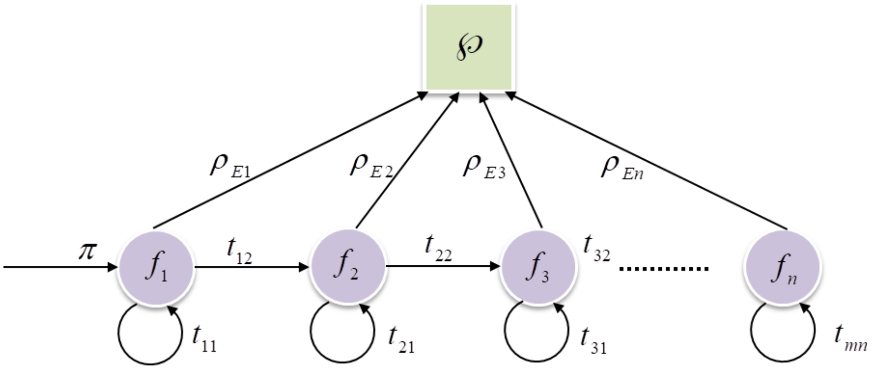


Figure 2. Structural design of PD-HMM

In the beginning, transition T, observation E, probabilities ρ , and initial probability array π are initialized, and HMM $(\lambda)$is described as,

$$\lambda = T, E, \pi \tag{6}$$

$$T = [t_{mn}], t_{mn} = \rho\left(\frac{f_\varepsilon = j_n}{f_{\varepsilon-1} = j_m}\right) \tag{7}$$

$$E = [e_m(L)], e_m(L) = \rho\left(\frac{g_\varepsilon = \vartheta_L}{f_\varepsilon = j_m}\right) \tag{8}$$

$$\pi = [\pi_m], \pi_m = \rho(f_1 = j_m) \tag{9}$$

Here, t_{mn}epitomizes transition matrix, $f_\varepsilon = f_1, f_2 \dots \dots f_n$ *and* $g_\varepsilon = g_1, g_2, \dots \dots g_n$ specify the fixed states and observation sequence, j_m, j_n exemplify the storing ρ of state n following state m, and $\vartheta_L$implies storing ρ of $E(L)$ being produced from n.

Thereafter, the Pareto Distribution function $(\wp) \to \rho(G|\lambda)$ for minimizing the interactions with positive real numbers $(\alpha)$is evaluated by,

$$\rho(G|\lambda) = 1 - \sum_{m=1}^{N} \alpha_\varepsilon^m \tag{10}$$

Now, equation (22) undergoes optimal backtracking with probability $(\rho *)$ which is represented as,

$$\rho *= \max_{1 \le m \le N} [\delta_\varepsilon(m)] \tag{11}$$

Afterward, $(\rho *)$ undergoes illustrative training to match offline and online maps of AV and gives information to navigate.

3.5. On Board Unit (OBU)

Prioritization and Localization are done in navigation through FSCH-KMC and CG-KF. The big data has dropouts in data storage and consistency. Therefore, HDFS is utilized that ensure data reliability and parallel processing by dividing large files into blocks and distributing them across a cluster to provide structured data for efficient clustering.

3.5.1. Prioritization

The FSCH-KMC algorithm is utilized for prioritizing the minimum distance signal in cases where unexpected objects suddenly appear in front of the vehicle. The algorithm mentioned in section 3.3 clusters nearby signals (γ_s) to curb speed in situations of the sudden appearance of objects in AVs.

3.5.2. Localization

Hence, by utilizing the CG-KF algorithm, the prioritized signals (γ_s) are localized. Conventional KF can handle nonlinear and non-Gaussian data, but it assumes the data as linear observation models, which is not realistic in real-world scenarios. Hence, to mitigate such an assumption, Cosine Gramian-KF is utilized. The CG-KF steps are as follows.

Initialization: Primarily, the state vector $\left(\vec{\aleph}_0\right)$ and state covariance matrix (Φ_0) are initiated as,

$$\vec{\aleph}_{c|c-1} = u_{sh}\vec{\aleph}_c + v_{sh}\lambda_c \tag{12}$$

Where, $\vec{\aleph}_{c|c-1}$signifies state estimate vector, $\vec{\aleph}_c$symbolizes state transition vector, u_{sh} and v_{sh} specify the state transition and control input matrix, and $\lambda_c$epitomizes control input.

Prediction: After initialization, $\vec{\aleph}_{c|c-1}$ and Φ are predicted utilizing a Cosine Gramian matrix (Q_c) with aZtime step. It is given by,

$$\Re_{c|c-1} = u_{sh}\Re_{c-1}u_{sh}^Z + \left[\frac{Q_c.Q_c^T}{\overline{Q_c.Q_c}^T}\right] \tag{13}$$

Gramian Updation: Now, Gramian matrix $(\mathfrak{I}_{sh})$ of u_{sh} and Φ_{sh} utilizing $\mathfrak{I}_{sh}$is updated by,

$$\mathfrak{I}_{sh} = u_{sh}u_{sh}^Z \;\&\; \Re_{c|c-1} = \mathfrak{I}_{sh}\Re_{c|c-1}\mathfrak{I}_{sh}^Z \tag{14}$$

Gain Estimation: From the above predictions, K gain using $\Re_{c|c-1}$and measurement covariance$\Phi_M$is estimated as,

$$\kappa_c = \Re_{c|c-1}M_{sh}^Z\left(M_{sh}\Re_{c|c-1}M_{sh}^Z + \Phi_M\right) \tag{15}$$

$$\Re_c = (I - \kappa_c M_{sh})\Re_{c|c-1} \tag{16}$$

Where, κ_c symbolizes Kalman Gain and M_{sh} epitomizes the measurement matrix for Z, which is required for time-to-time updation of AVL to navigate in the correct path. Hence, the proposed system provides SL and efficient navigation for AVs.

4. Results and Discussion

To validate the proposed model's performance and consistency, the entire research was conducted and tested on the Python platform, which provides a versatile and effective environment for coding, testing, and deploying a wide range of applications and tools.

4.1. Performance Analysis of AVL in SL

To show the effectiveness of the work, the proposed techniques' performance is included in this section. A performance comparison between the proposed GMCC and other prevailing techniques, namely ECC, Rivest-Shamir-Adleman (RSA), Digital Signature Algorithm (DSA), and ElGamal is given in Table 1. The conventional ECCs' security level is improved by the inclusion of the Montgomery curve together with the Gini coefficient. When compared to other models, the proposed model obtains a better security level of 98% and a lower attack rate of 3%. Moreover, GMCCs' shorter encryption and decryption times and lower memory storage requirements confirm better performance compared to others.

Table 1. Validation of GMCC

Methods	Proposed GMCC	ECC	RSA	DSA	ElGamal
Security Level (%)	98.63	96.57	94.24	92.15	89.25
Attack Level (%)	3.89	7.52	12.35	15.84	19.57
Encryption Time (ms)	1058	1365	1565	1765	1986
Decryption Time (ms)	1035	1325	1524	1741	1898
Memory Usage on Encryption (kb)	31924960	33117824	35697864	37332600	39774856
Memory Usage on Decryption (kb)	31396048	33890144	35531856	37643536	39852152

The proposed BN clustering performance is depicted by contrasting it with prevailing methods in Figure 3. Chi-Hell Square distance measurement tailored for centroid and distance calculation is employed in this work. This approach remarkably obtains 13247 milliseconds (ms) CT, outperforming KMC, Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH), Partition Around Medoids (PAM), and Fuzzy C-Means (FCM) that have longer CT of 17523 ms, 22354 ms, 26847 ms, and 29685 ms, correspondingly. Therefore, the proposed FSCH-KMC performed better than existing clustering methodologies.

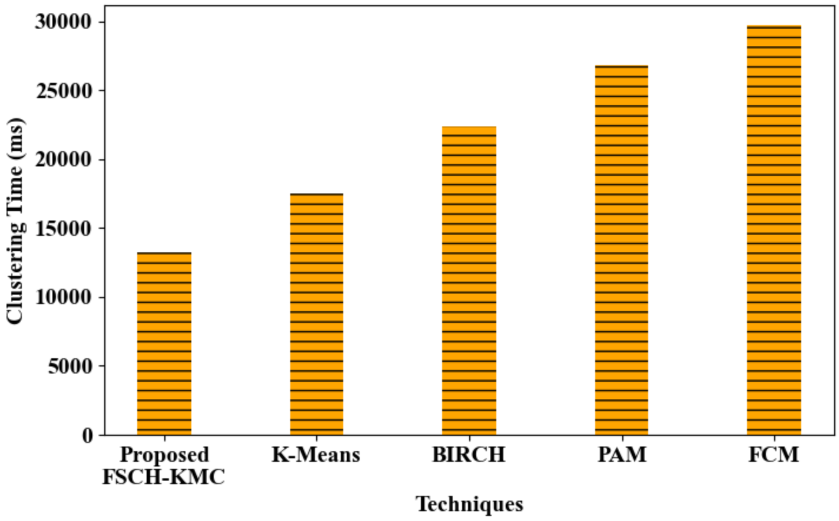
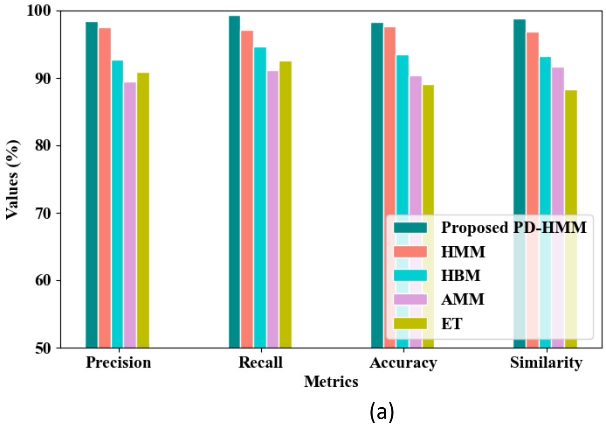


Figure 3. Clustering Time (CT) Analysis



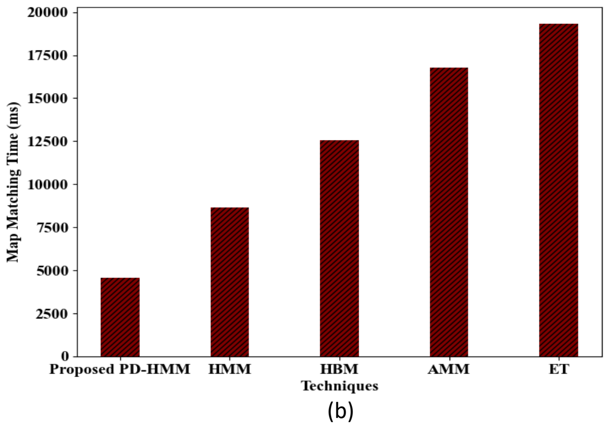


Figure 4. Comparative analysis of PD-HMM

The proposed PD-HMM algorithms' comparative analysis is exemplified in Figure 4(a). From this figure, it is evident that PD-HMM obtains impressive precision of 98%, recall of 99%, accuracy of 98%, and similarity rates of 98%, correspondingly. This superior performance can be attributed to the PD's implementation within the HMM framework. Contrarily, lower percentages in the aforementioned metrics are yielded by prevailing algorithms, namely Estimation Theory (ET), Andrey Markov Model (AMM), Hidden Bernoulli Model (HBM), and HMM. Likewise, from Figure 4 (b), considerably less time of 4578 ms is required by the proposed work for matching maps, while other methods consume more time. Thus, the proposed PD-HMM performs superior compared to other techniques, thus delivering better outcomes.

The efficiency of the proposed FSCH-KMC method that considerably reduces response and prioritization times during validation when contrasted with conventional techniques is highlighted in Figure 5. This speed enhancement is credited for the utilization of Chi-Hell Square distance measurement, thus facilitating quicker minimum distance signal selection. However, in AV applications, algorithms, such as K-Means, BIRCH, PAM, and FCM experience delays and challenges. Hence, the proposed method obtains a response time of 2145 ms and a prioritization time of 3587 ms, correspondingly, clearly illustrating its better performance over alternatives.

The performance of the proposed CG-KF's Processing Time (PT) and error rate meeting with prevailing methods, namely KF, Alpha Beta Filter (ABF), Kernel Adaptive Filter (KAF), and Covariance

Intersection (CI) is displayed by the graphs in Figures 6 (a) and (b). It uses Cosine-based G-KF that excels in handling real-life nonlinear and non-Gaussian systems. Particularly, the CG-KF obtains a low error rate of 0.08475% and a rapid PT of 3896 ms, thus outperforming other methods that exhibit higher error rates and slower processing times.

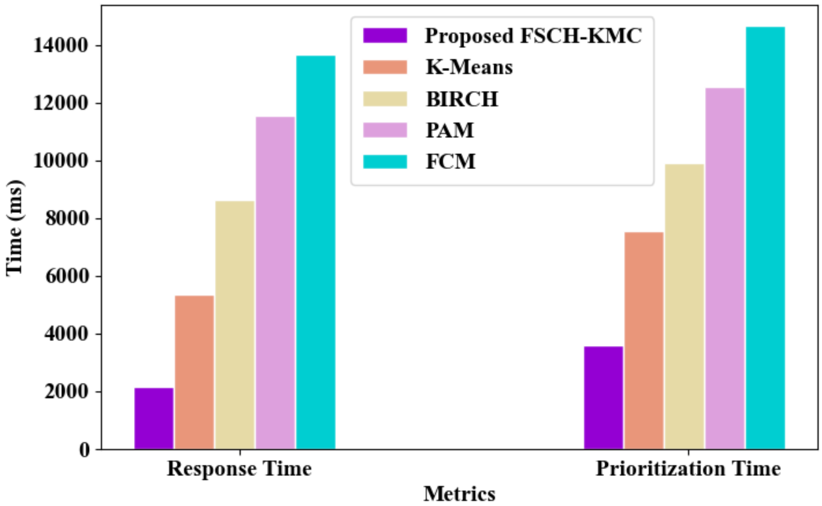


Figure 5. Response and Prioritization Time Investigation

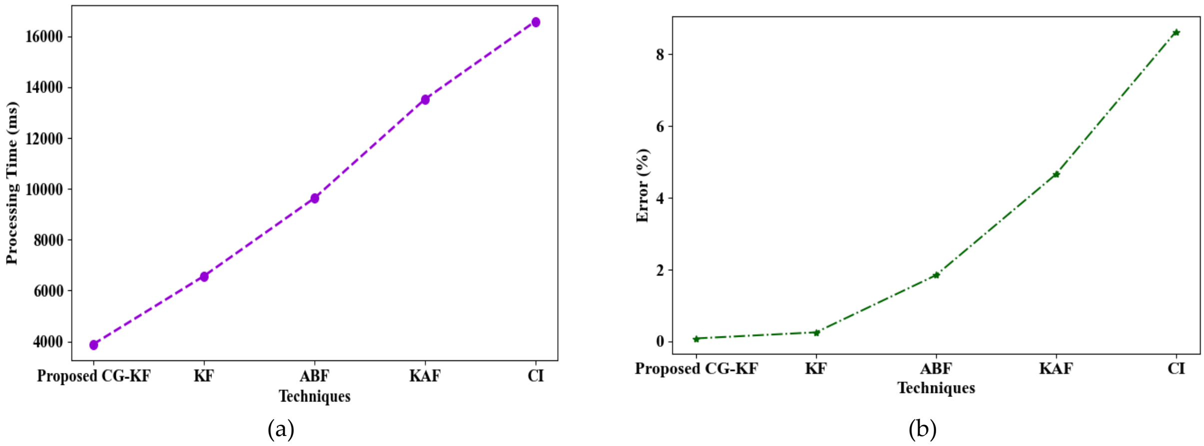


Figure 6. (a) Processing Time (PT); (b) Error Rate Scrutiny

Table 2. Comparative analysis with existing works

Techniques	Methods used	Precision (%)	CT (ms)	PT (ms)	Error (%)	Accuracy (%)
Proposed work	GMCC, FSCH-KMC, PD-HMM, and CG-KF	98%	13247	3896	0.08475	98%
(Chu et al., 2021) [16]	VL via Cooperative Mapping	-	-	-	0.6	80%
(Luo & Ko, 2022) [17]	USBL SLAM-based UKF	-	15423	-	0.15	-
(Wang et al., 2021) [18]	Box particle filtering of AVL with OSM	53%	-	6470	0.7	77%
(Vivacqua et al., 2018) [19]	BLMR-based Map Matching for SL	-	-	7660	0.401	97%
(Farag, 2021) [20]	RT-MCL based UKF	-	-	4745	0.3	-

In Table 2, the proposed work uses GMCC, FSCH-KMC, PD-HMM, and CG-KF for SL in AVL systems, obtaining an impressive precision and accuracy of 98%. It also illustrates an effective clustering time of 13247 milliseconds and a processing time of 3896 milliseconds, correspondingly, with a low error rate of 0.08475. Contrarily, differing levels of performance are exhibited by several alternative methods with some higher processing time and error rates of 0.6, 0.4, 0.3, 0.15, and 0.6 together with lower accuracy and precision, highlighting the clear superiority of the proposed approach. Therefore, the effectiveness of the proposed work of SL in AVs is confirmed by the experimental analysis.

5. Conclusion

This research proposed a robust and effective framework for ensuring faster and more secure Autonomous Vehicle Localization (AVL) in both GPS-available and GPS-denied environments. By integrating advanced algorithms, this framework offers substantial improvements over existing methods. For secure AVL, the Gini-Montgomery Curve Cryptography (GMCC) and Fisher Score Chi-Hell Square-based K-Means Clustering (FSCH-KMC) algorithms were utilized. The GMCC algorithm provided a significant security advantage, achieving a high security level of 99% and reducing the attack rate to only 3%. This demonstrates its effectiveness in safeguarding AVs from potential threats during localization.

Additionally, the FSCH-KMC algorithm played a critical role in optimizing navigation decision-making. It delivered the fastest localization time of 3587 ms, efficiently clustering signals based on minimal distances. This reduced the latency in signal processing, enabling AVs to make decisions swiftly and reliably. For navigating AVs, the Cosine Gramian-Kalman Filter (CG-KF) further enhanced the framework by ensuring rapid processing times of 3896 ms, with a low error rate of 0.084, demonstrating its accuracy and speed in real-time navigation tasks.

Collectively, these results show that the proposed framework outperforms existing AVL systems in terms of both security and processing speed, offering a comprehensive solution for fast, secure, and precise AV localization.

6. Future scope of work

Despite the promising results, certain challenges remain, particularly when localizing AVs under adverse weather conditions. Although the framework delivers faster and more secure AVL in optimal conditions, signal prioritization and localization can become increasingly difficult in varying weather scenarios. In the future, further research will focus on enhancing the localization process under harsh weather conditions by integrating more advanced sensor technologies and algorithms. This will enable the system to maintain its high performance in even the most challenging environmental conditions, ensuring continuous and reliable AV navigation.

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