SSRG International Journal of Recent Engineering Science
ISSN: 2349–7157 / https://doi.org/10.14445/23497157/IJRES-V11I3P106

Volume 11 Issue 3, 56-63, May-Jun 2024

Original Article

Satellite–Based Navigation Enhancement Employing Advancements in GPS and Integration with 5G Networks

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Received: 08 April 2024 Revised: 12 May 2024 Accepted: 24 May 2024 Published: 13 June 2024

Abstract *- Modern navigation and location-based services have been completely transformed by satellite-based navigation systems, most notably the Global Positioning System (GPS). In order to improve satellite-based navigation, this article examines the latest developments in GPS technology and how they integrate with 5G networks. Recent developments in GPS technology have greatly increased the precision, dependability, and accessibility of GPS signals. These developments include the launch of additional satellite constellations and upgraded signal processing methods. Improved coverage in indoor and urban locations, reduced latency, and increased data transfer rates are just a few benefits of integrating with 5G networks. Applications for augmented reality, real-time location-based services, and improved car navigation are just a few of the new features and services made possible by the integration of GPS with 5G networks. Moreover, the integration of 5G and GPS can boost the effectiveness and security of transportation networks, allow for more accurate asset tracking and monitoring, and improve location-based applications' overall user experience. All things considered, the combination of GPS and 5G networks marks a substantial development in satellite-based navigation, creating new channels for location-based applications and services. In this study, the Square Root Unscented Stable Filtering algorithm method was proposed for the integration of GPS and 5G to increase the network's dependability, accuracy, and efficiency in placement.*

Keywords *- Advancements, GPS (Global Positioning Systems), Communications, 5G generation networks, Navigation technologies, Satellites.*

1. Introduction

Applications for satellite-based navigation systems are numerous and include disaster relief, military activities, and transportation. One of the most extensively utilized is precise positioning data; it is provided globally via the Global Positioning System (GPS), a satellite navigation system. On the other hand, technological developments have resulted in the creation of enhanced constellations and integration with communication technologies, improving the capabilities of satellite-based navigation systems. When China, Europe, and Russia implemented their own satellite navigation systems, GPS became fully operational in 1995 (Elliott and Christopher 2006).

The Global Positioning System (GPS), run by the US government and offering worldwide coverage, is the most well-known GNSS. Other GNSS systems are NavIC (India), BeiDou (China), Galileo (European Union), and GLONASS (Russia). While each of these systems functions separately, they can also be combined to increase accuracy and dependability, which is a process known as GNSS augmentation. GNSS (Global Navigation Satellite System) receivers collect location and timing data from a constellation of satellites that send signals from space. These receivers use the location, velocity, and exact time of the receiver based on this data.

It is widely used for many different purposes, including agriculture, timing synchronization for telecommunications networks, surveying and mapping, and navigation for automobiles, ships, and airplanes. It is a necessary piece of technology in today's world due to its accuracy and dependability.

As GNSS is progressively used in civil aviation, more stringent requirements must be met to ensure safe flying. For aircraft navigation to be safe, integrity is just as important as precision. The needed navigation performance (RNP) standards for satellite navigation systems, which include availability, accuracy, integrity, and continuity, have been created by the Civil Aviation Authority. These standards are for integrity and correctness (Guo et al. 2019).

The precision needed for safety in civil aviation during CAT-III approaches and en route is measured in kilometers or meters, and the standards for integrity risk assessment fall between 10−4/h and 10−9/approach levels.

The commercialization of 5G networks is accelerating globally. 5G phone calls are seen by industry development drivers as the key to improving personal consumption experiences and the shift to a digitally industrialized economy. Globally speaking, 5G must be a crucial component of long-term growth in the industry for large economies. Business-wise, 5G will engulf hundreds of industries. Technically speaking, nevertheless, 5G needs to integrate other technologies further. Therefore, this white paper recommends that continual research on the follow-up and thorough evaluation of architecture evolution and function enhancement are crucial. Evolution of 5G. 5G Advanced networks. South Korea, the first nation to implement 5G, has accelerated the development of a 5G+ convergent ecosystem and advanced 5G united services. Japan keeps highlighting the importance of B5G (Beyond 5G) to society and people's way of life. Unlike other communication network generations, 5G is regarded as the cornerstone of the digital transformation of the industry. The biggest economies of the world have asked for 5G, citing it as a necessary component of sustained economic growth. The 2030 Digital Compass plan, for instance, was put up by the European Union and included guidelines for the digitalization of public services as well as the commercial sector. 5G was accepted by the European Union as the foundation for industry.

With the integration of GPS to 5G networks, many other applications across industries can be made possible, considering the special features of 5G, such as massive machine type connectivity (mMTC), ultra-reliable low latency (URLL), and improved mobile broadband (eMBB). Enabling smart Vehicles, Virtual reality and IoT applications, increasing the precision, dependability and accessibility of GPS signals.

More so, by connecting GPS and 5G networks, location capabilities can be improved. GPS positioning accuracy can be increased in indoor and urban canyon environments by using 5G networks to supply more data, such as base station locations and signal quality measurements. Moreover, 5G networks can provide dependable and quick data transfer between cloud-based applications and GPS devices, improving user experience overall.

2. Recent GPS Technology

Among the significant advancements are:

Multi-Constellation Reception: In order to increase accuracy and availability, particularly in difficult situations, modern receivers can concurrently use signals from numerous satellite constellations (such as GPS, GLONASS, Galileo, and BeiDou).

Real-time Kinematic (RTK): RTK methods achieve centimeter-level accuracy in GPS by utilizing a fixed base station to correct satellite signals in real time.

Precise Point Positioning (PPP): PPP is a method that relies on corrections from satellite-based or ground-based augmentation systems to achieve centimeter-level positioning accuracy with a single receiver.

Improved Satellite Signals: A few more recent GPS satellites transmit extra signals, like L5 signals, which offer better accuracy and dependability, particularly in crowded areas.

Augmented Reality (AR): By utilizing GPS technology, AR apps can deliver location-based information in real time, improving user experiences in interactive games, navigation, and other applications.

2.1. The Potential Application of a 5G Communication System with a GPS-integrated Navigation System

Indoor-outdoor integration for navigation and location shall undoubtedly be realized since 5G communication technology has advanced; it is crucial for the advancements of driverless technologies, smart city development, and mapping services.

Location Services: The field of location-based services has expanded beyond simple location placement to encompass in-car navigation systems, crisis assistance, transportation management, and other features that significantly improve daily convenience. The emergence of the use of 5G Location-based services through communication technologies has opened up new growth prospects. These include the creation of inertial navigation systems, 5G large-scale array base stations, integrated satellite navigation systems, and other sensor-assisted systems that will enable navigation and communication in both indoor and outdoor environments, improving the accuracy of location information services.

Smart Cities: 5G is essential to the smart city, as it ushers in the era of the Internet of Everything and allows for high-speed connectivity. The Internet of Everything allows for the creative integration of big data, artificial intelligence, and cloud computing.

The construction of smart cities aims to improve quality by utilizing intelligent technology, information technology, and creative concepts to integrate the integrated city's management and service systems, allocate resources efficiently, and optimize resource utilization when building smart cities, the integrated navigation-system based on 5G technology will allow for the effective transfer of data pertaining to location. In addition to guaranteeing urban transportation, ecological environment safety monitoring, and other aspects.

Driverless Technology: This is the automation of driving a vehicle without the need for human intervention. It makes use of a variety of sensor technologies, artificial multidisciplinary technologies such as pattern recognition, navigation and positioning, and intelligence technologies. The limitations of conventional integrated navigation and positioning precision prevent it from fulfilling the requirements of self-driving vehicles. The swift advancement of 5G has also propelled autonomous technology to unprecedented heights of development. In addition to transmitting data gathered by other sensors using the fast network speeds and minimal latency of 5G technology, autonomous technology can also work in situations when the satellite navigation system signal is blocked. Inertial navigation, 5G millimeter wave positioning, and other vision sensors, when paired with 5G large-scale array antenna technologies, can significantly increase the precision of unmanned vehicles' positions.

The image below depicts a 5G hybrid locating situation using GNSS (GPS).

2.1.1. Models Used in Integrating GPS and 5G for Advancement in Satellite Navigation Systems

Several mathematical models and methods are used in the integration of GPS and 5G to improve positioning efficiency, accuracy, and dependability. The following are a few of the most important mathematical models and algorithms:

Kalman Filtering

To increase positioning accuracy, 5G and GPS signals are frequently integrated using Kalman filters. They are employed to determine the status of a dynamic system from a collection of inaccurate measurements. Kalman A common technique in navigation filtering algorithms is filtering, which is an optimal state estimation procedure. However, because it is limited to solving linear issues, it leads to interference with navigation's precision of position. As a result, numerous researchers have put forth numerous enhanced filtering algorithms.

Owing to unscented Kalman's efficient processing capability and straightforward computation for nonlinear systems, the enhanced UKF (Unscented Kalman Filter) algorithm of the BP (Back Propagation neural network) neural network is appropriate for systems that fluctuate in time, and the BP neural network is straightforward and traditional. The best Kalman algorithm is the Sage-Husa adaptive Kalman filter exhibits a straightforward concept and strong real-time performance. The addition of the square root version of the physical correlation enhances the numerical stability of UKF. The Square Root Without cent robust filter method eliminates the need to factory the state correlation at every phase by explicitly propagating the square of the root of it. Two further advantages of the square root form are statistical consistency and optimistic semi-certainty of the state covariance. When merging GPS and 5G measurements, the filter's stability must be guaranteed. Therefore, in order to warrant the trustworthiness of the SRUSF, a stability factor is infused as a little adjustment. In this paper Square Root Unscented Stable Filter will be employed.

Particle Filtering

In nonlinear and non-Gaussian systems, particle filters—also referred to as sequential Monte Carlo methods—are employed for state estimation. To increase positioning precision, they can be utilized in conjunction with GPS and 5G signals.

Artificial Neural Networks (ANNs)

ANNs, such as BP neural networks, can be utilized for signal processing, error correction, and data fusion, among other tasks, in the integration of GPS and 5G.

Machine Learning Algorithms

For classification and regression tasks pertaining to GPS and 5G integration, It is possible to use machine learning techniques, including random forests and Support Vector Machines (SVMs).

Signal Processing Techniques

A range of signal processing techniques are applied to GPS and 5G data in order to extract information for location., including digital filtering, correlation analysis, and wavelet analysis.

Optimization Strategies

GPS and 5G integration systems can be made to operate more efficiently by using optimization strategies like simulated annealing, particle swarm optimization, and genetic algorithms.

Probabilistic Models

To improve integration, probabilistic models like Markov models and Bayesian networks can be employed to simulate the uncertainty and variability in GPS and 5G data.

The combination of these mathematical models and algorithms improves the way GPS and 5G signals are integrated for a range of uses, such as location-based services, tracking, and navigation.

Square Root Unscented Stable Filtering Algorithm

Unscented evolution is presented in SRUSF. The mean and covariance terms are computed using the deterministic "sampling" method. The approximate choice of points for sample sites and the weights applied to them are determined by the following fundamental principle, which also allows for the recording of the significant statistical characteristics of the previous random variables. According to the square root breakdown of priori correlation., 2L + 1 sigma points are chosen. Applying the nonlinear function on every sigma point results in a cloud of modified points. By weighing the affected points, The dynamically adjusted mean and correlation can be computed.

From the column of system state matrix sGNSS5G (t_k) we can obtain 2 L + 1 points

$$\begin{cases} x_i = m + (\frac{x_0 = m}{\sqrt{(L+\lambda)}})ii = 1,\ldots,L \\ x_i = m\sqrt{(L+\lambda)}i - Li = L+1,\ldots 2L \end{cases}$$

Calculating the corresponding weight for each sigma point, the starting point of the system GPS&5G[t0] ∼ N

$$W_o{}^{(m)} = \frac{\lambda}{(L+\lambda))}$$

$$W_o{}^{(c)} = \frac{\lambda}{(L+\lambda)+(1-a_2+\beta)}$$

$$W_i{}^{(m)} = W_o{}^{(c)} = \frac{1}{2(L+\lambda)}, i=1,\ldots,2L$$

(m, P) has a Gaussian distribution with variance P and mean m.

Where λ = α2 (L + κ) − L is the expression for the scaling parameter. L is the size of the allotment of sigma, which tally close to the estimated value, is determined by α and κ in the state space matrix. A smaller positive value of 1 × 10−4 ≤ α < 1 is usually assigned to the parameter α. The scalar parameter β is used to include previous knowledge on likelihood distributions over the system's state space, and κ is an extra scaling parameter that is frequently set to 0. The optimal value of β for a Gaussian distribution is 2. The nonlinear function propagates these sigma vectors.

$$y_i = h(x_i)i = 0,\ldots \tag{5}$$

The state-prediction covariance of the joint positioning inaccuracy of the GNSS-5G can be expressed as

$$P -_{\square} (t_k) = FP(t_k)FT_{\square} + Q(t_k) \tag{6}$$

When the estimation-error covariance is denoted by P[t_k], its square root form R[t_k] is shown below, and Q[t_k] [is the clatter array of the Gaussian process at

$$P(tk) = R(tk)(R[t_k])^T \tag{7}$$

The square root of the state forecast correlation may be stated by Implementing the QR breakdown.

$$R-(t_k) = (qr\{[FR[t_k]\sqrt{Q[t_k]}^T\})^T \tag{8}$$

Where the MATLAB function "qr" (orthogonal triangular analysis) represents the QR decomposition, the process noise in the GPS and 5G combined the SR-USF algorithm's positioning is made up of two components: the stochastic clamor and the deterministic clamor. While the random clamor attributable to the sculpting inaccuracy needs to be precisely adjusted, one way to settle deterministic clamor is by employing prior information.

The expected mean and covariance of the innovation may differ from their real values in practice as a result of this modeling error. In order to tackle this issue, a stable coefficient is suggested here, which will surely increase this method's competitiveness.

$$R(t_k) = \sqrt{\phi(t_k)}R -_{\square} (t_k) \tag{9}$$

The calculated covariance of innovation e Pγ,γ[t_k] should, in order to maintain consistent estimates, be more greater or the same as the true one Eγ[t_k]γ T [t_k].

$$\mathrm{Prr}(t_k) \geq E\{r(t_k)rT_{\square}(t_k)(t_k)\} \tag{10}$$

$$r(t_k) = y(t_k) - y(t_k) \tag{11}$$

Where y^[tk] is the anticipated measurement and γ[tk] is the innovation sequence. It is important to note that the covariance of innovation can be expressed as:

$$\mathrm{P}_{r,r}(t_k) = H(t_k)P(t_k)H^T(t_k) + Q(t_k) \tag{12}$$

Where P[t_k] represents the cross-covariance within the observations and the anticipated state covariance, and Px,y[t_k] represents the predicted state:

$$P_{x,z}(t_k) = P(t_k)HT_{\square}(t_k) \tag{13}$$

connecting hypotheses (12) and (13) points to hypotheses

$$\mathrm{Pr}, r(t_k) = P^T{}_{r,y}(t_k)P^{-1}(t_k)P_{x,y}(t_k) + Q(t_k) \tag{14}$$

Equation (15) is produced by integrating across Equations (10) to (14), and the hazy element added to the expected state covariance its meant to satisfy the condition.

$$\kappa(t_k) \geq \frac{E\{y(t_k)y^T(t_k) - Q(t_k)}{(P^-{}_{x,y}(t_k)^T(P^-(t_k)^{-1}P^-{}_{xy}(t_k)} \tag{15}$$

Where P −[t_k] denotes the projected state's covariance. P[t_k] In the absence of the fading component, $P_{x,y}$[t_k}] = ϕ[t_k]P⁻ x,y [t_k}], and $P_{-x,y}$[t_k}] is the cross-covariance of the measurement and state.

It is therefore shown that modeling error can be minimized by using the lower bound of the stabilized coefficient $\upsilon[t_k]$ determined in Equation (15) as long as the innovation's estimation consistency is maintained. The expected measurement covariance's square root can be found using Equation (8).

$$R_{y,y}(t_k)=\left(qr\{[y'(t_k)\sqrt{U(t_k)}]^T\}\right)^T \tag{16}$$

$$y'(t_k)+[(y(t_k)]_0-y(t_k)\ldots[y(t_k)]i-y(t_k)\ldots \\ [y(t_k)]2L-y(t_k))\, x\, diag\left(\sqrt{W^{(c)}}\right) \tag{17}$$

Where L is the receiver's dimension. (y[tk]) Here, i, i = 0, 1, 2L represents the propagating sigma value, and the expected measurement results are represented by y[tk]. The noise matrix of Gaussian measurement at tk is denoted as U[tk]. The sigma points weight is shown by √ W(c). One may compute the state correlation is calculated from QR breakdown using the:

$$R(t_k)=\left(qr\{[x^*(t_k)-y^*(t_k)\ K(tk)\ \sqrt{U(t_k)}]^T\}\right)^T \tag{18}$$

$$X^*(t_k)=\left[(x(t_k))_o-s(t_k)\ldots(x(t_k)i-s(t_k)\ldots(x[t_k]_{2nx}-s(t_k)\right]x \\ diag\left(W^{(c)}\right) \tag{19}$$

where $K[t_k]$ indicates the propagating sigma points and $(\chi[t_k])i$, i = 0, 1,..., 2L is the advantage from filtering.

3. The Square Root Unscented Stable Filtering Algorithm for the GPS and 5G Positioning

Initialization denotes the estimated state of GNSS and 5G joint positioning and its square root of the prediction error covariance at t_k by s*GNSS&5G (t_k) and R(t_k). For every iteration k= 1,…,T (1) The prior estimate for predicting the state of the system and the square root of its covariance are as follows:

Sgnss&5g(t_k) = FsGNSS&5G(t_{k-1})

$$R^-(t_k)=\left(qr\left\{\left[FR(t_k)\sqrt{Q(t_k)}\right]^T\right\}\right)^T$$

(2) Generate 2L + 1 sigma points

$$x^{-(i)}(t_k)=s^-GNS\ \&\ 5G^{(t_k)}$$
$$X^{-(t_k)}=s^-GNS\ \&\ 5G^{(t_k)}+\sqrt{\lambda+L}(R^-[tk])i$$
$$X^{-(L+i)(tk)}=s^-GNS\ \&\ 5G^{(t_k)}+\sqrt{\lambda+L}(R^-[tk])i$$

Where I = 1,…,L

(3) Propagate the sigma points in the GNSS-5G joint positioning model

$$y-(i)(tk)=hGNSS\&5G(X-(i)(t_k))i=0,1,\ldots,2L$$

(4) Evaluate the predicted value of the measurement result

$$\hat{y}^-(t_k)=\sum_{i+0}^{2L}W_i^{(m)}\left(y^-(t_k)\right)i$$

Where $W_i^{(m)}$ is the means weights of the sigma points.

(5) Compute the innovation

$$r-(t_k)=y(t_k)-\hat{y}-(t_k)$$

(6) Calculate the cross-covariance

$$P^-_{x,y}(t_k)=\sum_{i=0}^{2L}W_i^{(c)}\left(\left(X^-[t_k]\right)_i-\bar{\hat{S}}(t_k)\right)X\left(\left(y^-[t_k]\right)_i-\hat{y}[t_k]\right)$$

(7) Create a balanced figure and add it to the state prediction's square root covariance.

$$R[t_k]=\sqrt{\varphi[t_k]}\,R^-(t_k)$$

(8) Employ the newly projected state to generate the new sigma points, and then repeat steps 2 through 6 to continuously produce new design and cross-covariance.

(9) Determine the design covariance's square root.

$$R_{y,y}(t_k)=\left(qr\left\{\left[y^*(t_k)\sqrt{U(t_k)}\right]^T\right\}\right)^T$$

(10) Calculate the Kalman gain and update the GNSS and 5G estimate state

$$K(t_k)=\left(P_{x,y}(t_k)/R_{y,y}(t_k)\right)/R^T_{y,y}(t_k)$$
$$s(t_k)=s^-(t_k)+K(t_k)r(t_k)$$
$$R(t_k)=\left(\left\{\left[x^*(t_k)-K(t_k)y^*(t_k)K(t_k)\sqrt{U(t_k)}\right]^T\right\}\right)^T$$

4. Simulation Results and Discussion

This section assesses how well SRUSF performs in GPS and the 5G joint positioning model in terms of positioning error and estimates errors of measurements under various circumstances. The simulation scenario and parameters are set up in Section 4.1, and the benefits of the suggested SRUSF algorithm are verified in Section 4.2. The data is processed using MATLAB 2022a, and the setup of the computer is as follows: Windows 10 (64-bit), Intel i5-10400H (CPU), and 24 GB of RAM.

4.1. Configuring the Parameters

For positioning, TOA/AOA readings from 5G BSs and pseudo-range measurements from GNSS are fused. Table 1 provides a summary of several crucial parameters for simulation for GPS and 5G BSs. The 5G Positional Reference Signal (PRS), which complies with 3GPP TS38.211, is the transmit signal.

Table 1. Parameters

Parameters	Value
5G carrier frequency	3.5 GHz
5G bandwidth	100 MHz
Subscarier Spacing	30 KHz
Total number of satellites	10
Total number of 5G BSs	10

There are 1000 s in total that the simulation lasts. The 5G PRS and GNSS update rates are fixed at 1 Hz. The GPS-5G joint positioning receiver travels at a speed of two meters per second in the x direction. The clock skew noise σ has a standard deviation of 1 ns. Only the visual line Since the observation-screening and NLOS-suppression functionalities are absent; conditions are simulated.

4.2. Evaluating Performance

We assess the suggested hybrid positioning method's accuracy in horizontal localization across several simulated scenarios and contrast it with seven cutting-edge techniques, such as the conventional EKF, MRAKF, UKF, SRUKF, VBHUKF, and SRUSF. Check to make sure it functions correctly. While this research focuses on 2D settings, it can easily be extended to 3D scenarios. (1) How well the multiple-signal joint functions estimating technique is compared with the other five approaches' cumulative distribution function (PDF), location inaccuracy, and recommended method. From Figures 3 and 4, we can deduce that the arrangement technique EKF distillation, which has the biggest placing inaccuracy in the plane among the confluence of the six observations approaches for GPS and 5G collaborative placing and in ninety percent of the cases1.98 meters, is the horizontal positioning error. This is most likely due to some precision loss occurring when the system model's EKF computes the observation matrix using the Jacobian matrix. This may be caused by the necessity for the EKF to infer the Jacobian matrix in order to acquire the matrix of findings, which will cause some precision loss. When comparing MRAKF to EKF, because the average root mean square error (RMSE) is less than 0.4 m, adaptive filtering is beneficial. Since UKF uses the UT transform to lessen accuracy loss due to nonlinear challenges, it is far more accurate than standard EKF. In 90% of the situations, the plane placing inaccuracy is 1.55 meters. Arranged to achieve self-adaptation, VBHUKF estimates the covariance of time-varying measurement noise using the variable Bayesian approximation. In contrast compared to UKF, it offers a positioning precision that is roughly 10% greater and better filtering consistency. In order to guarantee the state space covariance matrix's semi-positive qualitative value, SRUKF adds the covariance form squared into UKF. This results in more reliable numerical output placement fidelity is much superior to alternative techniques and just marginally better than SRUKF; the recommended SRUSF achieves a positioning inaccuracy of 0.97 meters, which outperforms the other five filtering methods in 90% of instances. This is mostly because we have suggested a tight-coupled filter group in an inventive manner. To produce an ideal positioning estimate, the observations from each signal source are fused after being separately filtered by the GPS and 5G joint positioning receiver. At the same time, the stabilized coefficient is included in the state prediction covariance updating process. It will surely lessen the likelihood that the filtering results would diverge since the system model and the real world are not perfectly matched, eventually improving the positioning accuracy within the algorithm.

The main focus of this work is the association between the quantity of placement accuracy in the received positioning signals and the GPS and 5G joint positioning system. It also looks at how various fusion location algorithms affect the outcomes. The relationship between the number of placement indications and the exact location in the horizontal planes is shown in Figure 5.

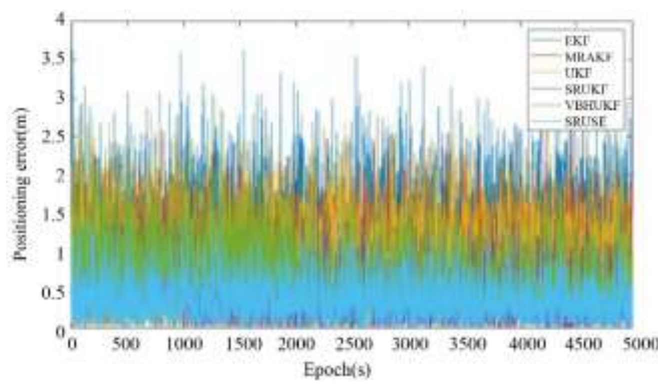

Fig. 3 Positioning error comparison of EKF, MRAKF, UKF, SRUKF, VBHUKF, and the proposed SRUSF method

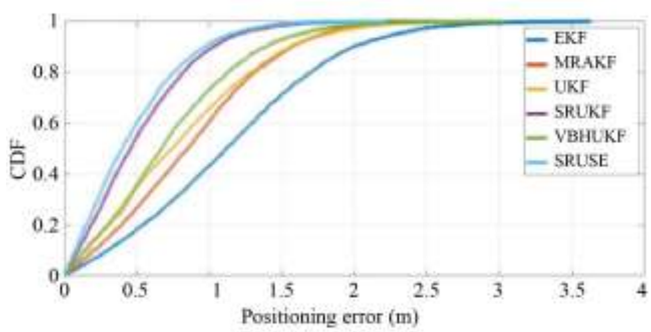

Fig. 4 CDF of positioning error for EKF, MRAKF, UKF, SRUKF, VBHUKF, and the proposed SRUSF method

(2) Performance in positioning with varying numbers of accessible signal sources.

The following variables have a direct impact on the GPS-5G joint positioning's positioning inaccuracy system: the measurement error, the system model's modeling accuracy, the positioning method, the number of visible signal sources, the signal source's geometry, and the error in signal transmission. The first three items are outside the purview of this work and have to do with baseband signal processing algorithms and system design parameters.

A key factor influencing positioning mistakes is also the geometric distribution of signal sources. However, the effect on location mistakes is negligible in optimal circumstances where the signal sources are dispersed equally.

The article focuses on the correlation between the combined GPS and 5G positioning system's positioning accuracy and the amount of positioning signals received. It also examines the effects of various fusion localization strategies regarding the outcomes. Figure 5 shows how the amount of relationship across the number of placement indications and the exact location in the horizontal planes relate to each other.

It is evident that as the receiver receives 10 positioning signals instead of three, each fusion's positioning errors rise method drastically reduces positioning accuracy and does not significantly increase with additional available positioning signals. In contrast to the approaches EKF, MRAKF, UKF, SRUKF, VBHUKF, and SRUSF, the suggested SRUSF algorithm performs as comparable to that of other techniques. However, the SRUSF algorithm's good numerical stability performance makes it superior to the other techniques.

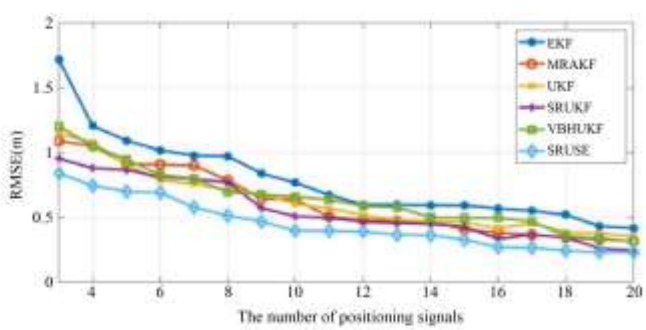

Fig. 5 Positioning RMSE versus the number of positioning signals with different me

GPS and 5G cooperative positioning results in a standard setting. Three common GNSS and 5G combined positioning scenarios— the modest and substantial occlusions of satellite signals, respectively —are examined in this section to further demonstrate the advantages of the SRUSF method suggested in these research communications, as well as the severe blocking of satellite transmissions. We demonstrate how different positioning algorithms work in various settings and simulate varying numbers of visible satellites. If the base station of the 5G IS dispersed equally surrounding the positioning receiver. It can be configured to meet the appropriate requirements. It is difficult to track how shifts in the number of GPS satellites affect location when there are too many base stations in the system.

We provide 3 varieties of analysis data, including varying degrees of correctness. The result of the real placement mean is set to zero, and the standard deviations are set to 0.5, 0.4, and 0.3 meters. The sky plan and the Taylor in the three common scenarios diagrams are provided.

5. Conclusion

Our goal in this study was to offer a combination processing solution for GPS and 5G signals to facilitate the wide application of a very reliable network. Ensuring better positioning, timing and navigation.

There is a lot of potential in the suggested method for multiple-signal joint estimates. The extremely trustworthy PNT operations for large consumers within the GPS-and-5G-base mesh structure will be greatly aided by this article.

Funding statement

This research was funded by the authors.

Acknowledgement

Special thanks to the Almighty God for making this possible. In the same vein, I appreciate my supervisors, Dr. (Mrs) Ifeoma Asianuba and Dr. Matthew Ehikhamenle, for the unwavering support they gave me to make this a success. More so, I won't fail to mention my husband, who supported me financially and mentally. Crucial in that order are my parents, Prof and Prof (Mrs) Uba Nwuba. Special thanks to the Editor of IJRES and his team.

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