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Optimum Model for Tracking of Moving Objects

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Abstract-. **In wireless communication, it is a challenge to find the accurate position of moving objects. The present work proposes that the global positioning system (GPS) receiver to measure the position and velocity of moving objects. These measurements are dynamic, and the Least Squares (LS) technique is used to linearize the measurement for further processing. The time difference of arrival (TDOA) methodology was also applied. The obtained data is then processed through a Kalman filter to mitigate non-line-of-sight errors and smoothen the range values. The Kalman filter applies standard deviation on received data and performs an NLOS/LOS hypothesis test. By processing the received data, the algorithm generates readings that mitigate the NLOS error and reduces position error. The proposed recursive tracking algorithm will be comparatively more robust to measurement errors because it updates the technique that feeds the position corrections back to the Kalman Filter. It compensates for the measured geometrical position and decreases random error influence to the position precision for tracking of moving objects. The simulations demonstrate that the proposed algorithm reduced the noise by 28.64% and 34.4% in LOS and NLOS regions respectively. These findings indicated that the accuracy of object tracking was significantly improved as compared to other algorithms while also being less computationally intensive and cost-efficient.**

Index Terms— **Global Positioning System (GPS), Time Difference of Arrival (TDOA), Kalman Filter, Line of Sight (LOS), Non-line of Sight (NLOS).**

I. INTRODUCTION

Determining and tracking the precise location of non-stationary objects is still a focal point of many researchers. There have been numerous methodologies developed and utilized to accurately track mobile items [1]. Amongst these, the Global Positioning System (GPS) is one of the most popular ones [2]. However, this method has its drawbacks regarding accuracy errors.

One of the main reasons this area of research remains such a hotbed of research activity is the fact that Radio Frequency Interference has become increasingly difficult to deal with via current techniques. Due to the increasing reliance on radio communication, the atmosphere has become polluted with numerous radio frequencies that interfere with one another thereby increasing the noise surrounding the position tracking of any object [3].

Three factors affect the ability to track any object – Motion sensors, GPS units, and the tracking algorithm. Among these three, the one factor that is lacking behind the other two is the tracking algorithm. Since the sensitivity of the motion sensors and the GPS units is at its most advanced due to technological advancements, the tracking software is the limiting aspect that prevents accurate tracking of moving targets. Due to this, researchers have tried to augment the accuracy of current algorithms by combining different types together with the hopes of combining the benefits and mitigating the drawbacks of each of those algorithms [4]. One of the major effects that impact the accurate tracking of moving objects is the multipath fading effect. In areas, where Non-Line of Sight (NLOS) is present like in the vicinity of multiple high-rise buildings, tall trees, or tunnels, the signal from the base is reflected off several objects before it reaches the receiver. This creates multiple paths from the initial signal that can have distorted frequencies, amplitudes, and phases at the receiver end resulting in perceived noise. This effect is especially detrimental to non-stationary object tracking as the multipath fading effect is amplified due to the motion of the receiver [5]. Hence, the primary objective of this research is to minimize the multipath fading effect and thus reduce radio frequency interference through post-processing the signal via powerful algorithms.

The GPS is one of the most popular tools utilized for object tracking however it is limited by the number of satellites used. This limitation results in an average accuracy of 5 to 10 meters from the target object where there are few hindrances for the GPS signal and a significantly reduced accuracy when NLOS exists [6]. Due to the popularity of GPS and its receivers, researchers have kept a keen focus on integrating this technology with various other tracking methodologies to solve the accuracy conundrum [7]. However, this dilemma remains unsolved despite the greater use of wireless communication and the development of various technologies such as the 4G/5G networks.

TABLE I
LITERATURE REVIEW

Author	**Title**	**Methodology**	**Shortcomings**
Peng Wu at el [8]	Time Difference of Arrival Localization Combining Weighted Least Squares and Firefly Algorithm	This paper proposes a hybrid firefly algorithm (hybrid-FA) method, combining the weighted least squares (WLS) algorithm and FA.	The proposed algorithm works to reduce the computational power the for localization of TDOA. It also increases the accuracy the of target. But it does not work on NLOS tracking.
Zou J et al [9]	“Mobile Location Estimator with NLOS Mitigation using Kalman Filtering”	The method involves identifying the propagation channel using a Gaussian Mixture Model (GMM), followed by a limiting filter to mitigate the Non-Line-of-Sight (NLOS) error, and finally, regression is used to smooth the positioning result.	The proposed method does not explain its implementation, computation time, accuracy under specific conditions, comparison with existing methods, scalability, or generalizability to different scenarios
Noha El Gemay el at al [10]	“A Hybrid TDOA/RSSD Geolocation System using the Unscented Kalman Filter”	With the help of TDOA and Received Signal strength difference (RSSD) geolocation is estimated and by the use of an Unscented Kalman filter (UKF), hybrid geolocation is investigated.	The method suffers from large errors in many scenarios. There is also the absence of the effect of unknown path loss exponents which may be investigated in estimating the exponent as a parameter in the Kalman Filter
Kandur i at el [11]	“Evaluation of TDOA based Football Player's Position Tracking Algorithm using Kalman Filter”	The Gauss-Newton method is used for solving nonlinear least squares problems more efficiently compared to Newton's method and the Kalman filter is applied for optimal recursive data processing.	The Antenna arrays are located at various positions on the ground and also require a lot of transmitters that attach to players. It increases the cost.
Fokin et al [12]	“TDOA measurement processing for positioning in Non-Line of Sight Conditions”	Developed and verified of three-stage TDOA measurements processing algorithm for positioning a transmitter when there are up to two receivers with NLOS measurements and taking into account actual path loss.	The abstract mentions that the investigation did not take into account non-line-of-sight (NLOS) conditions and the effects of signal power loss due to propagation.

The objective of the presented work is to improve the accuracy of position-tracking algorithms. Before beginning on improving the accuracy, it is important to understand what factors affect the result. As mentioned before, the two major forms of Radio Frequency (RF) wave transmission are Line-Of-Sight (LOS) and Non-Line-Of-Sight (NLOS). During LOS, the transmitting antenna radiates the RF wave directly to the receiving antenna, with no hindrance present between them, while an NLOS condition occurs when there are hindrances present between the receiver and transmitter. As a result, it can be understood that during the LOS condition, the error is mostly represented by the Time-Difference-Of-Arrival (TDOA) noise. This noise can be easily simulated via a “Zero Mean Gaussian Random Variable” allowing us to readily study it, predict it, and solve it. However, during an NLOS condition, the RF wave undergoes various phase, frequency, and amplitude changes due to its interaction with the environment caused by reflection, diffraction, and scattering. Therefore, it results in unpredictable noise known as path loss which is amplified the more the RF wave interacts with its environment. Due to this, it makes it difficult for the tracking algorithms to remove such noise as random error is extremely difficult to navigate resulting in poor accuracy.

Keeping in consideration the issues faced by GPS tracking, this research aims to contribute the following to position tracking:

1. A hybrid approach that combines GPS, and Kalman filter to predict the position of a moving object.
2. Remove the convergence issue when objects move in a non-line-of-sight environment (NLOS).
3. Enhancing the accuracy of position estimation of moving objects.

The research motivation is to minimize the errors of tracking any object and estimate its location when it is in NLOS condition. This research aims to provide optimum and cost-effective solutions for accurate target tracking of moving objects.

This paper is organized as, Section I has an introduction and related work. Section II explained the methodology, and the results are provided in Section III. While the last sections (Sections IV and V) conclude the proposed research work and recommendations for future work respectively.

II. METHODOLOGY

The most common trilateration method that is used to locate any object on earth is a Global position system (GPS). At least 03 satellites are required in this method for calculating the location of the object on earth. In Fig. 1, three large circles represent the footprints of satellites shown behind the earth map. The common point where circles bisect each other indicates the position of the target object on Earth. If the number of satellites increases, then object position accuracy is improved.

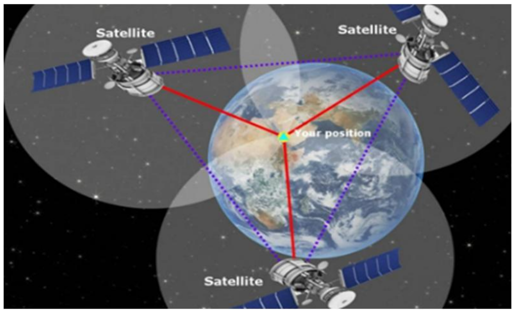

FIGURE 1. GPS Calculating the position of an object by trilateration method

Despite being extremely common, GPS is affected by several prominent factors that reduce the accuracy of its object-tracking abilities. Some of these major ones include the long distances between the satellites and the earth (thousands of Kilometers) resulting in weak signals at the receiver, the presence of uneven atmospheric conditions, and a continuous threat of signal jamming. These factors only exacerbate the noisy effects caused by NLOS conditions such as an object being present in compact areas like rooms (resulting in signals bouncing off a lot of other objects), in the middle of a forest, under a tunnel, or in a cityscape [13].

Hence, the main objective of this research work is to mitigate the NLOS error thereby improving the accuracy of tracked objects. We propose using the Kalman filter to resolve these issues as it is a cost-effective solution that is also computationally less intensive and more efficient as compared to other algorithms [14]. However, before we can apply the Kalman filter we must figure out how to exactly locate an object via GPS. The best way to do this is by calculating the Time Difference of Arrival (TDOA) which is calculated by determining the difference in arrival time of signals between different emitting sources [15].

A. PROPOSED FRAMEWORK

This research work specifically investigates the position of moving objects by GPS measurement system and focuses on improving the accuracy of moving objects by investigating GPS positioning accuracy and by modifying the Kalman filter algorithm as illustrated in the flow diagram in Fig. 2. Traditionally, the least squares method is used to solve equations for GPS positioning. However, this study proposes a modified Kalman filter algorithm as an alternative approach to improve the accuracy of moving objects.

In phase I, the Global Positioning System (GPS) receiver is connected to some form of an intelligent electronic system such as an Android 4 G-enabled phone. However, to receive GPS signals, a dedicated application must be installed such as the MATLAB Sensor Acquisition app. Once these prerequisites have been met, the receiver (Android phone) can be used as a trackable object where its GPS data can be gathered and stored onto a dedicated MATLAB cloud server for future use. In phase II, the stored GPS data of the phone is extracted from the cloud and stored locally for further processing. MATLAB processing techniques are utilized to convert raw GPS data into an executable form that can be used to develop a geographic plot. However, this geographic plot is not compatible with the Kalman filter, so it is converted into a Cartesian plot. Lastly, in phase III, the Cartesian plot data is passed through the Kalman filter and converted into a Cartesian set. This set is then used to provide comparative results with position and velocity errors. The results compare the position estimates with and without the Kalman filter being applied.

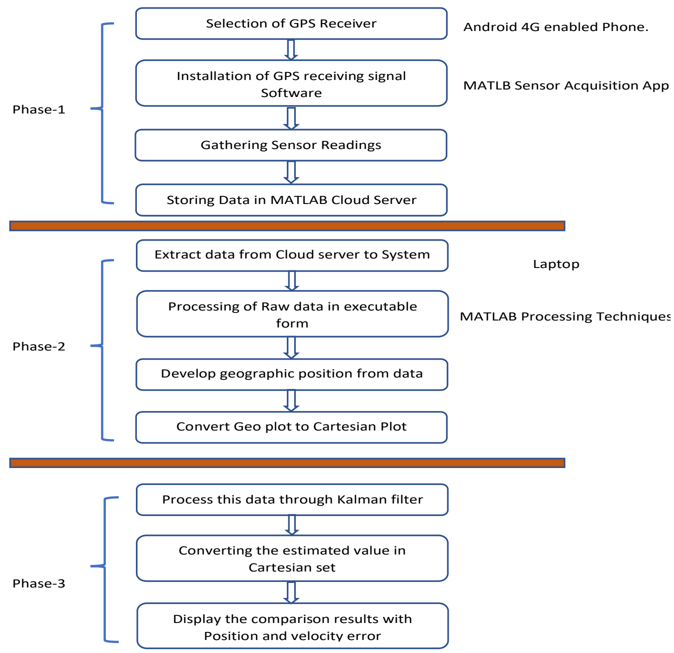

FIGURE 2. Flow diagram of Proposed Methodology

The GPS receiver starts working by capturing signals transmitted by GPS satellites through an antenna. The signals are then amplified to the required strength and matched with the output frequency from a chain of radio frequencies. Afterward, the signals are processed through software and converted into a digital format using an analog-to-digital converter (ADC). During the acquisition stage, the receiver can identify specific satellite signals, which are tracked to determine the transition phase of navigation data. Subsequently, sub-frames and navigation data are obtained from the navigation data. Ephemeris and pseudo ranges data can be extracted from the navigation data, which assists in determining the satellite's position. Ultimately, the receiver's location can be calculated by acquiring the satellite's position and pseudo ranges data.

The following equation (1) will determine the receiver's location:

$$d_i = \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} + Ct \quad (1)$$

x1, y1, z1, and d1 are the coordinate locations of the GPS receiver and pseudo ranges will be obtained from the movement of a transmission signal. 'C' is the speed of light and 't' is the receiver clock bias.

The method of least squares is a technique used to approximate solutions for over-determined systems, where there are more equations than unknowns. It is often used in data fitting, where the aim is to find the best fit between modeled data and observed data in a least-squares sense, meaning that the sum of the squared residuals is minimized. A residual is the difference between the observed value and the value predicted by the model.

In GPS, the observation equation is non-linear, making it a non-linear least squares problem. To find the position and clock error of a GPS receiver using the least squares method, the non-linear least squares (NLS) algorithm is used.

$$d_1 = \sqrt{(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2} + Ct$$

$$d_2 = \sqrt{(x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2} + Ct$$

$$d_3 = \sqrt{(x - x_3)^2 + (y - y_3)^2 + (z - z_3)^2} + Ct$$

$$\ldots$$

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} + Ct \qquad (2)$$

where (x, y, z) are the coordinates of the GPS satellite in the 'Earth Centered Earth Fixed (ECEF) frame' and d_i is pseudo range observation, a subscript is a satellite number and has value$1,2,3, \ldots, N$. (x_i, y_i, z_i) is the GPS receiver position in the ECEF frame. In Equation (2), $'d_i'$ is calculated from the GPS receiver, (x, y, z) are precisely calculated from ephemeris data and are four unknowns needed to be found by solving the equations. Obviously, Equation (2) is non-linear and there are usually more than four satellites being tracked or in view, making it an overdetermined problem. In simpler terms, we have more information than we need to solve the problem, and the equation is complex and requires solving four unknowns. When dealing with a non-linear least square problem, there is no analytical solution available. Therefore, numerical algorithms are used to compute the values of (x_i, y_i, z_i, t) that minimize the sum of squared residuals, denoted by M. The residuals are the differences between the measured GPS receiver distances $'d_i'$ and the distances computed using the (x_i, y_i, z_i, t) values. In simpler terms, we use numerical methods to find the best-fit values that minimize the difference between the measured and computed distances.

$$M = \sum_{i=1}^{n} r_i^2 \qquad (3)$$

Residual value is given as:

$$r_i = d_i - \widehat{d_\iota} \qquad (4)$$

The algorithm for finding the true values involves an iterative process, where initial values for these parameters are chosen. The predicted pseudo range value corresponding to the estimated values is then calculated. In each iteration, Equation (3) is linearized by approximating it to a first-order Taylor series expansion around the current estimate of $(\hat{x}_i, \widehat{y_\iota}, \widehat{z_\iota}, \hat{t})$. The Jacobian matrix J changes with each iteration. The iterative algorithm begins by determining an initial approximate value and its corresponding pseudo-range value $\widehat{d_\iota}$. The algorithm then refines these values by successive approximation until the true values of $(\hat{x}_i, \widehat{y_\iota}, \widehat{z_\iota}, \hat{t})$ are found [16].

$$\hat{d}_i = \sqrt{(x - \hat{x}_i)^2 + (y - \hat{y}_i)^2 + (z - \hat{z}_i)^2} + C\hat{t} \qquad (5)$$

To denote the difference between the true values $(x_i, y_i, z_i, t)$and the estimated values $(\widehat{x}_i, \widehat{y_\iota}, \widehat{z_\iota}, \hat{t})$, we use the notation $(\Delta x_i, \Delta y_i, \Delta z_i, \Delta t_i)$ and $\Delta d_i = d_i - \widehat{d_\iota}$, respectively [17]. By linearizing (2) around the estimated values$(\hat{x}_i, \widehat{y_\iota}, \widehat{z_\iota}, \hat{t})$, we obtain a first-order approximation of the equation.

$$\Delta d_1 = h_{x1}\Delta x_i + h_{y1}\Delta x_i + h_{z1}\Delta x_i - Ct_i$$

$$\Delta d_2 = h_{x2}\Delta x_i + h_{y2}\Delta x_i + h_{z2}\Delta x_i - Ct_i$$

$$\vdots \qquad \vdots \qquad \vdots$$

$$\Delta d_n = h_{xn}\Delta x_i + h_{yn}\Delta x_i + h_{zn}\Delta x_i - Ct_i \qquad (6)$$

Let:

$$\Delta d = [\Delta d_1 \quad \Delta d_2 \quad \ldots \quad \Delta d_n]^T,$$

$$\Delta X = [\Delta x_i \quad \Delta y_i \quad \Delta z_i \quad -C\Delta t_i]^T,$$

$$H = \begin{bmatrix} h_{x1} & h_{y1} & h_{z1} & 1 \\ h_{x1} & h_{y2} & h_{z2} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ h_{xn} & h_{yn} & h_{zn} & 1 \end{bmatrix}$$

Above equation can be written in matrix notations.

$$\Delta X = (H^T H)^{-1} H^T \Delta d \qquad (7)$$

NLOS solution is given in the following.

$$(x_i, y_i, z_i, t) = (\hat{x}_i + \Delta x_i, \widehat{y_\iota} + \Delta y_i, \widehat{z_\iota} + \Delta z_i, \widehat{t_\iota}, -C\Delta t_i) \qquad (8)$$

Initial values have a chance of large errors, so repetition based on the initial value is required to achieve closer to a true value. These values can be achieved nearly after 10 repetitions.

The Kalman filter is a mathematical algorithm that can recursively process new measurements as they arrive. Its predictor-corrector estimator is designed to minimize the estimated error covariance and is regarded as optimal. Using observed range data and determining the true range value, the Kalman filter can be used to estimate the state vector of a mobile target [18].

X_{k+1} vector (size 2 × 1) that shows the position or state of the object and W_k vector (2 x 1) that indicates the input of the Kalman Filter.

The state or position vector:

$$X_{(k+1)} = A_k X_k + B_k W_k \quad (9)$$

$$A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \; B = \begin{bmatrix} 0 \\ \Delta t \end{bmatrix} \quad (10)$$

where $X_k = [L_m(k) \quad \hat{L}_m(k)]$ is the state vector of the moving object, related to m^{th} sensor. The W_k is the process noise vector with a covariance matrix $Q = \sigma_w^2 I$, as shown in Fig. 3. $y_{(k+1)}$ is the measured data that represents the predictable GPS interpretation at time t_{K+1} [19].

The measurement process is

$$y_{(k+1)} = C_k X_k + U_k \quad (11)$$

The A and B matrices are transition matrices of size 2 × 2 that relate the current state and input to the next state, and the C matrix is the predictable state to the next GPS measurement, and U_k is the measurement noise with covariance $R = \sigma_v^2 I$.

$$C = [1 \quad 0] \quad (12)$$

Kalman Filter is a powerful method used to estimate the status of a system by combining noisy sensor outputs with uncertain dynamics. It consists of three main components: prediction, observation, and estimation. The Kalman filter is a linear and optimal algorithm that minimizes the variance of state sequences in dynamic systems. The dynamic system is mathematically described by the state equation and observation equation. The Kalman filter uses a combination of prediction and measurement to estimate the current state of a system while minimizing errors caused by uncertainties in the system [20].

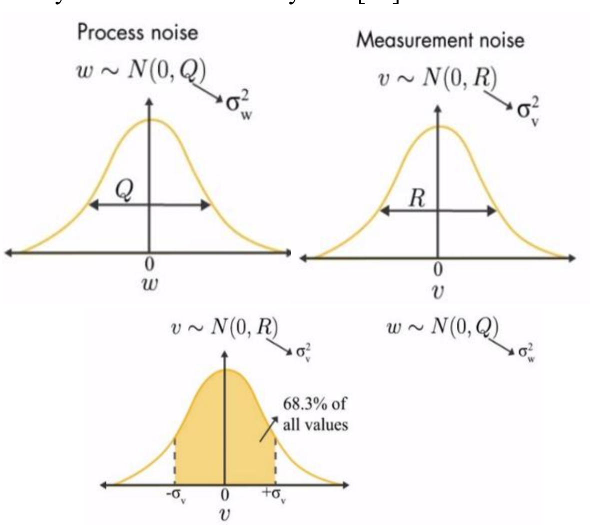

FIGURE 3: Process noise and measurement noise covariance.

Kalman filter operation is given as follows.

First-time update by filter

$$\boldsymbol{\hat{X}_{(k|k-1)} = \widehat{AX}_{(k-1|k-1)}} \quad (13)$$

The prior estimate error covariance is then

$$\boldsymbol{P_{(k|k-1)} = AP_{(k-1|k-1)}A^T + BQB^T} \quad (14)$$

The measurement update equation of the filter is:

$$\boldsymbol{K_{(k)} = P_{(k|k-1)}C^T \left[CP_{(k|k-1)}C^T + R_k\right]^{-1}} \quad (15)$$

The matrix $K_{(k)}$ minimizes the posterior estimate error covariance and it is the Kalman gain vector,

$$\boldsymbol{\hat{X}_{(k|k)} = \hat{X}_{(k|k-1)} + K_k\left[y_{(k)} + C\hat{X}_{(k|k-1)}\right]} \quad (16)$$

$$\boldsymbol{P_{(k|k)} = P_{(k|k-1)} - K_{(k)}CP_{(k|k-1)}} \quad (17)$$

W here $K_{(k)}$ is the Kalman gain prediction and $P_{(k|k)}$ is the covariance matrix of $\hat{X}_{(k|k)}$[20].

Kalman filter modified the ranges according to previous process data fed to it.

The uncertainty of an object's position is represented by the variation in the discrepancy between the time update estimate of the Kalman Filter and the GPS receiver measurement as follows [21]:

$$\text{Error} = y_{(k)} - CX_{(k|k-1)} \quad (18)$$

The error value will reflect the multipath effect in the GPS receiver measurement. The number of these values should be neither too small nor too large to well represent the uncertainty of the recent position estimation [22]. When there is no multipath effect on an item, the GPS accuracy is good, the error values are small, and they are nearly equal. As a result, there won't be much variance in the error values. However, the accuracy of the GPS will be considerably impacted and the error values will be completely and randomly different. As a result, the error values will be large [23].

The error between the GPS receiver's measurement and the location estimate is reflected in the difference between the estimated position in the first stage and the actual measurement. The presence or absence of a multipath impact may depend on this divergence.

Condition-I: If

$$y_k - CX_{(k|k-1)} > 0 \cdots \textit{Non Line of Sight condition}$$

Then

$$X_{(k+1)} = AX_k + BW_k$$

Condition-II: If

$$y_k - CX_{(k|k-1)} < 0 \cdots \textit{Line of Sight condition}$$

Then

$$\hat{\sigma}_u^2(k) = \sigma_u^2(m) \tag{19}$$

III. RESULTS AND DISCUSSION

MATLAB has been used for the proposed model simulation. In a 2 min sampling period, 100 samples have been considered. The velocity of the moving object is 4m/s. The data is obtained at three known receiving stations, and it is shown in Table II.

TABLE II
PARAMETERS OF MOVING OBJECT DATA RECEIVED FROM GPS SENSOR

Data Recording Time	Latitude	Longitude	Altitude	Speed	Course	hacc
06:42:41.000'	24.92848	67.15408	36.2	8.514	315.27	2.2
06:42:42.000'	24.92854	67.15402	36.2	8.902	317.76	2.1
06:42:43.000'	24.9286	67.15396	36.3	8.973	317.55	2
06:42:44.000'	24.92866	67.15389	36.4	8.971	314.66	1.9
06:42:45.000'	24.92872	67.15383	36.6	8.911	313.14	1.9

The plot is oriented such that the starting point of the journey is located at the origin (0, 0) (Fig. 4). As the object moves toward the West, its position is represented by a negative value on the x-axis. Similarly, as the object moves toward the South, its position is represented by a negative value on the y-axis. This convention of using negative values to represent movement toward the West and South is commonly used in Cartesian coordinate systems. It allows us to represent the position of an object relative to a fixed point, such as the starting point of a journey, and to easily visualize its movement in different directions. Here it may be important to note that the starting position of the object has some drift from the (0,0) position due to a conversion error from a spherical to 2D Cartesian system.

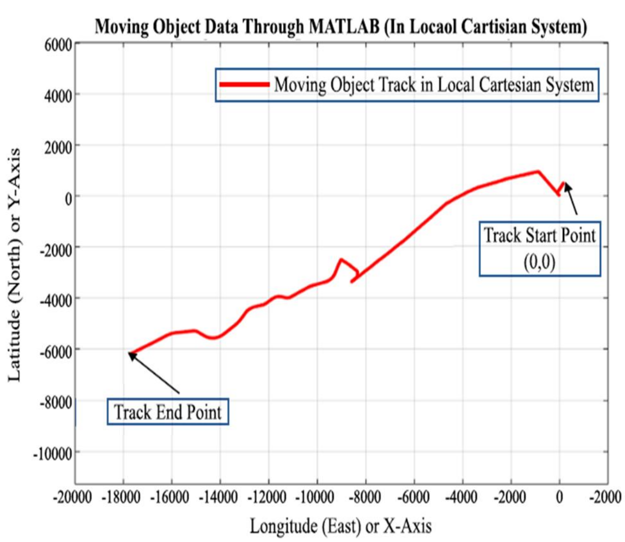

FIGURE 4: Real-time Cartesian plot of moving object tracking.

At 1150 seconds, the object is nearly in a stopped condition, which causes a glitch in the reading. However, the Kalman filter value follows the actual readings, which indicates that the filter is effectively smoothing out the noise and improving the accuracy of the measurements.

The error in the velocity reading is approximately 1.765 m/s. This error represents the difference between the measured velocity and the true velocity of the object. The Kalman filter is designed to estimate the true value of the velocity based on the noisy measurements and the mathematical model as Equations (9) and (10) used to describe the movement of the object and velocity error between measured and true velocity as shown in Fig. 5.

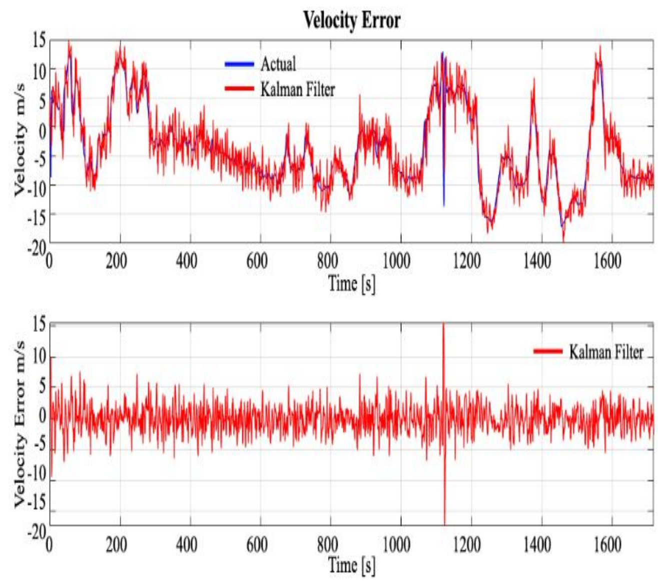

FIGURE 5. Velocity Error.

The actual travel of the object is in the west direction and its Kalman filter estimate and estimation error concerning velocity is shown in Fig. 5.

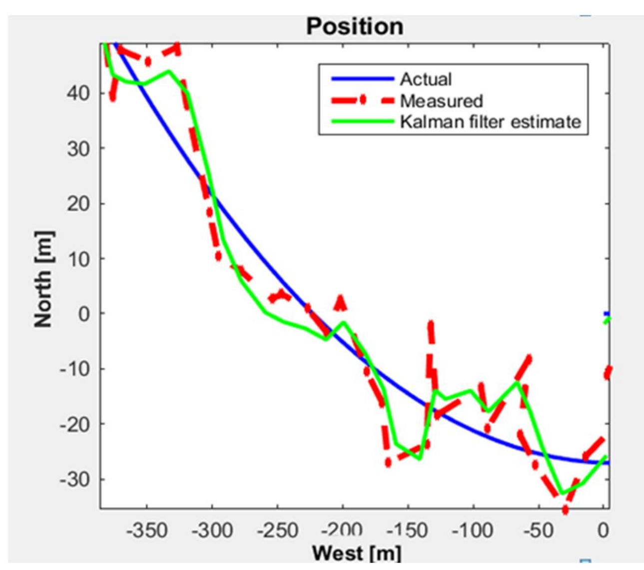

FIGURE 6. Position estimation.

Fig. 6 illuminates the use of the Kalman filter as (18), which distant the NLOS error. The solid line and dashed pattern represent the actual position and Kalman estimation position respectively.

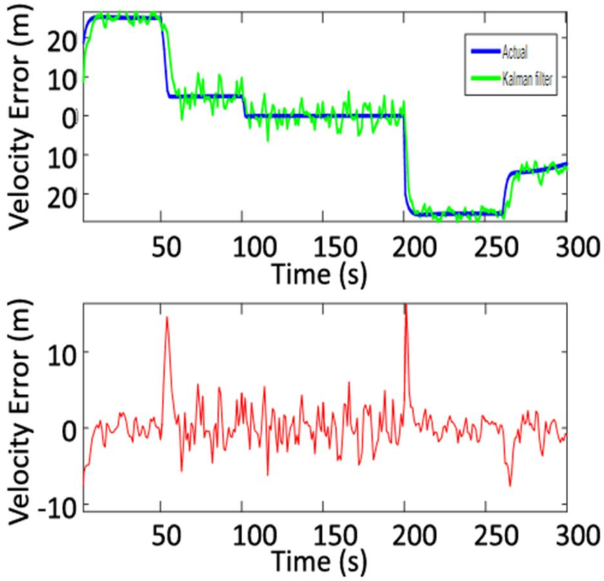

FIGURE 7. NLOS mitigation using Kalman filter.

Fig. 7 shows the mitigation of NLOS error by applying the Kalman filter algorithm to increase the estimation. It can be observed that the filter enhanced the accuracy.

TABLE III
WITHOUT KALMAN FILTER ERROR STATISTICS

Environments	Distance (m)	Standard deviation Error (m)	Mean Error (m)
- A1 (Open Area)	1000	1.32	2.23
- B1(High Buildings)	200	17.71	28.40
- A2 (Open Area)	300	4.11	9.23
- B2 (High Buildings)	200	21.20	24.02

Table III and Table IV, provide a comparative result of the GPS techniques. In Table III, the state-of-art positioning techniques were utilized without the Kalman Filter while in Table IV the Kalman Filter was applied to the same positioning techniques. The control variables in both scenarios are the environments that the object passes through. A1 represents the first open area where the signal is received unhindered. This allows us to set a baseline for clean data without any noise carrying over from any previous environment. B1, on the other hand, is the first time the object passes through a region of high buildings that distort the signal and introduce noise. A2 is the second open area region where the algorithm is given some time to return to baseline and get rid of the noise developed in B1. The real testimonial of positioning techniques is however illuminated in B2 when the object returns to a high-building region. This is because, in this region, the algorithm must deal with not only the newly developed noise from NLOS but also the previously carried-over noisy data from B1. As a result, this means that the better a technique can return to baseline in A2, the better it will perform in B2 as it will have to deal with less noise.

In Table III, the positioning techniques are utilized without using the Kalman Filter meanwhile in Table IV, the Kalman Filter is applied as a post-processing measure. It can be noted that the standard deviation and the mean error are drastically higher in high-building regions in the presence of the multipath effect. Additionally, the Kalman Filter technique is better equipped at returning to baseline in open areas such as A2. This allows it to deal better with high-building regions such as B2. In Table II, the mean error and standard deviation error are significantly higher in the B2 region which can be attributed to the inability of the position techniques to get rid of the noise developed in B1 while they were in A2. As a result, as soon as the object entered the second area of high buildings, the positioning techniques that have recursive learning models reintroduced the noise back into the data leading to even higher noise.

In contrast, Kalman Filter was able to clean the data better in A2 thus allowing the model to return to a better baseline. Due to this, when the object entered B2 environment, the mean and standard deviations did not increase to the pre-Kalman Filter levels. Although, a dramatic increase can be observed the overall performance is better which indicates an improved overall positioning model.

TABLE IV
WITH KALMAN FILTER ERROR STATISTICS FOR THE POSITION ESTIMATION

Environments	Distance (m)	Standard deviation Error (m)	Mean Error (m)
- A1 (Open Area)	1000	1.12	2.01
- B1(High Buildings)	200	7.41	15.13
- A2 (Open Area)	300	3.54	9.13
- B2 (High Buildings)	200	17.23	13.02

IV. CONCLUSIONS

The objective of research work is to identify the location of moving objects with maximum accuracy. This research work has measured the position and velocity of moving objects with the help of a GPS receiver. It was observed that due to the presence of noise and NLOS conditions, there is a drift in the measured value concerning actual values. To minimize this variation, the measurement of GPS has been pre-processed and passed through the Kalman filter.

Kalman filter has processed this measurement and reduced the noise error, the reduction of noise in the east and north is 28.64% and 34.4% respectively, and 1.765 m/s velocity error concerning the original value.

The Kalman filter has applied to the GPS measurements to estimate the true state of the moving object, which was its position and velocity. By considering the uncertainty in the measurements and the dynamics of the system, the Kalman filter reduces the noise error and improves the accuracy of the estimates, and mitigates the NLOS conditions. The reduction in noise and error translates to improved reliability and safety in such systems. This research work highlights the potential of this approach in enhancing the required precise positioning and navigation. However, the accuracy of the filter's estimates is reliant on the quality of the measurements and the accuracy of the model, which should be taken into consideration when implementing this approach.

V. FUTURE WORK

The work done in this research can be extended in many ways. The simulation results show that the TDOA technique is eligible for the position estimation solution. The statistical parameters that are set up for various environmental situations are a major factor in the correction algorithms. When more than one position locating method is employed to locate the mobile units, such as the combination of the AOA and TDOA methods, the research of various information-combining techniques may be another direction for advancement. In such hybrid systems, the overall position location solution must be able to incorporate the data from both approaches in a way that prevents the inaccuracies in the results from both ways from adding to one another and negatively impacting the overall position estimation solution. The combined location estimation fix that results from this should be more precise than the fixes from the individual two-solution approaches. Only one base station may occasionally be able to pick up the mobile signal in certain circumstances. Combining AOA and TOA procedures is one of the options suggested for such circumstances. The TDOA approach, however, may be used in situations where installing antenna arrays is not essential by using receivers in the cell just to obtain signal snapshots. In addition to the base station receiver itself, at least two other receivers are required for the TDOA approaches. Using the suggested method in the real world appears to be a promising possibility. However, several issues need to be addressed.

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CONFLICTS OF INTEREST

The authors declare they have no conflicts of interest to report regarding the present study.

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