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Integrated Navigation System (INS) And Global Positioning System (GPS) Using H-Infinity Filter

Lakshmi Shrinivasan [1], Reshma Verma[2] , M D Nandeesh[3] , Divya M N[4]

[1] Associate Professor of Department of ECE, MS Ramaiah Institute of Technology, India,

[2] Assistant Professor of Department of ECE, MS Ramaiah Institute of Technology, India,

[3]Assistant Professor of Department of EIE, MS Ramaiah Institute of Technology, India,

[4]Assistant Professor of School of ECE, REVA University, India,

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Abstract

The global positioning system is gaining wide importance these days in the navigation of vehicles from their starting point to their destination. This service is free of cost and can be used in any part of the world. It gives accurate measurements like position, time constraints on the ground as well as in space. GPS satellite functioning is that it transmits signals to the respective receivers; these signals need a clear view so that they perform well in an open environment like forest areas. Inertial navigation systems (INS) consist of motion sensors like accelerometers and gyroscopes it is provided with initial information like position, the velocity of the object moving from the GPS satellite. However, GPS has certain limitations like the GPS outage problem, which results in jamming and other problems, which weaken the system. To encounter these issues, the fusion of data techniques is carried out with the help of filters by incorporating AI techniques to attain better performance as well as to predict the navigation purposes. In the GPS/INS datasets considered here, the data is preprocessed with the help of H_∞ filter. GPS outage issue is solved by these filters, increasing the precision, and estimating the position of GPS. The results obtained after the experimental analysis show that the position of GPS is predicted accurately, by considering the vehicle measurement data and its path on the MATLAB framework.

Keywords – GPS, INS, Global Positioning System, GPS outage, Inertial navigation systems

1. INTRODUCTION

Recently, the widespread use of GPS to authorize the navigation system to be more precise and commercial for military applications. [1] To position the vehicles on a navigation system given the description. GPS signals are affected by various external factors like climatic conditions, which can affect them resulting in noise that deteriorates the performance. While the GPS signals have deteriorated, they affected the performance of moving vehicles a challenging task. [2-3] INS (independent navigation system) is not affected by external environmental factors. These keep a track of the position of the vehicle, the velocity at which the vehicle is moving, and acceleration estimation. These issues led to the integration of GPS and INS algorithms for efficient GPS signals for navigation purposes.

From the early '90s, the integrated GPS and INS algorithms are an outstanding accomplishment that is fed into navigation devices making them more effective to use. These integrated devices [5-9] upon incorporating artificial intelligence within the lead in successful navigation of vehicles from one point to another without losing upon external factors. This method can be used in all commercial devices required for navigation purposes.

The GPS signal which is not corrupted from the external noise, the system employs an integrated mechanism for navigation of vehicles. [10-12] The accuracy of integrated navigation relies upon the precisive nature of the GPS signal as well as the inertial estimation unit. When the GPS signal is corrupted or not functional the system shifts towards IMU for navigation. This results in GPS outages which leads to weakening the system without compensating it. To fill these gaps, we make use of Kalman filtering $\mathbf{H}_\infty$ mechanism for effective prediction.[15-17] Kalman filtering technique as well as AI and ML techniques are initiated for the estimation of its location, velocity of the vehicle, and its acceleration capacity for GPS outages. The integrated GPS and INS algorithms are extensively used in broad areas of applications like vehicle navigation systems and various other fields.

This model [18-20] is deployed resulting in ambiguity and no presence of noise in the numerical character, which leads to loss of strength, and assurance in Kalman filtering. From this problem, we can conclude that the performance of execution is compromised even though to achieve accuracy to such an extent in achieving a non-sequential approach deployed on a system to identify the parameters. The Kalman filter does not require any external data such as noise as it is strong enough for integration mechanism, the EFKF mechanism with the presence of addition of noise in the signal for processing, and game theory is also known as minimax theory is used for evaluation.

It is very well understood that no models can effectively necessitate a platform; many methods are carried out for exploring this filter. To counter this problem two methods are used for Riccati process and the linear max inequality process. By comparison of this, we make use of the MATLAB framework to solve this problem. The first region is the control region for $\mathbf{H}_\infty$
Hypothesis. By the addition of ML makes it more predictable and increases the accuracy in measures of velocity, the position of reference, and acceleration parameters. According to the accomplished knowledge here we can conclude that there can be no extensive search carried out rigorously for $\mathbf{H}_\infty$ filter that is to be a not balanced effect on INS/GPS model, acknowledge a word which is associated for estimating the hypothesis.

2. RESEARCH METHOD

Our main goal here is to link the output generated from INS resulting in particular information of data. To predict a GPS outage, a well-trained AI module along with necessary information is used. The integrated module of GPS and INS is thoroughly studied, and here the AI module is trained by the GPS signal.

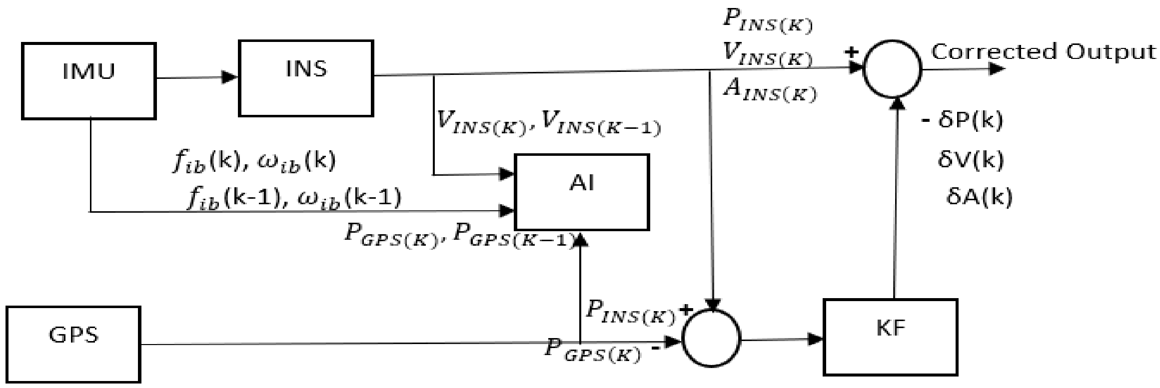

Fig .1 Kalman filter training mechanism

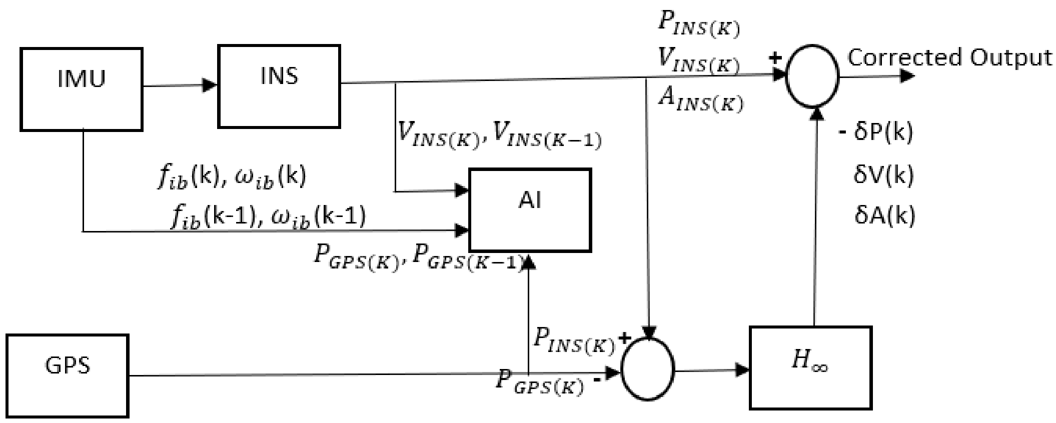

Fig .2 $\mathbf{H}_\infty$ filter training mechanism

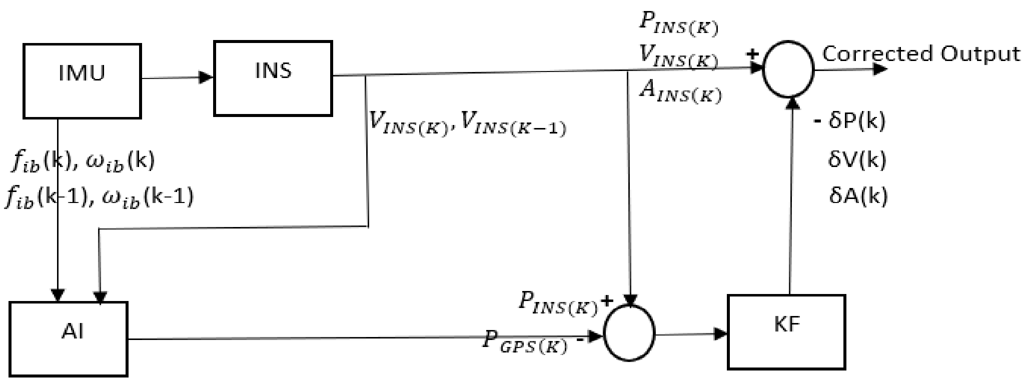

Fig .3 Kalman filter prediction mechanism

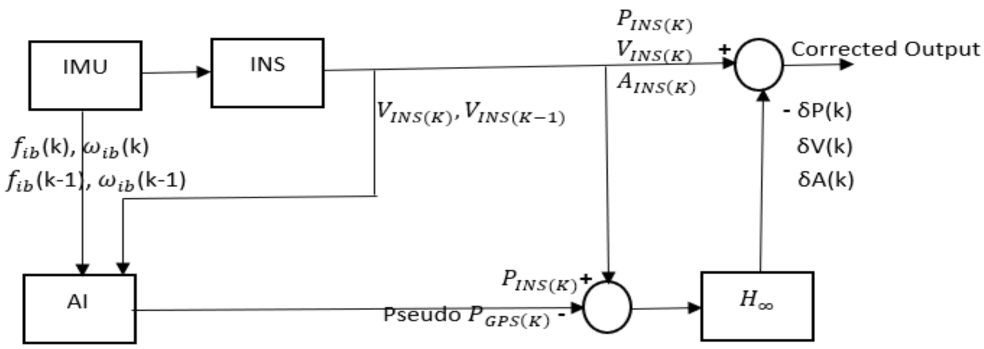

Fig .4 $\mathbf{H}_\infty$ filter prediction mechanism

This navigation system is widely used for vehicles with the combination of GPS signals along with the INS signals. In our proposed scheme, we have compared the Kalman filter and $\mathbf{H}_\infty$ filter and AI module. The GPS signal is functioning; the combined INS signals for navigation of vehicles and GPS signals efficiently train the AI module, used for the prediction of related information essential for navigation, while suffering from a GPS outage. During a certain point, the relevant data generated from the output fed to INS is related to the change which is obtained from GPS and INS information. In [22] we can state that a model O_{INS} -δP_{INS} there are used to find the relationship between the GPS and INS.

Here in Fig. 1, a trained model is shown while a GPS signal is used V, P, A which indicate velocity, the position of the signal, and acceleration are shown. Here K indicates the time, $K - 1$ states the previous time constrain, and the error estimated is shown byβ**.** For integrating, the information received from GPS and INS outage. While GPS signals are, functioning estimated velocity, position, and acceleration error is used for correction of the output generated from the hybrid system. Training the inputs generated as a result from IMU and INS navigation signal systems an AI module is used, where K and $K - 1$ sample data is considered f_{ib}, velocity and angular rateω_{ib}, this output gives the result of the GPS position, which is incremented.

Fig. 2 the illustration of a training model is shown with $\mathbf{H}_\infty$ during the occurrence of GPS outages. The AI model collects the data as output from INS information; these are an accurate force f_{ib} the velocity of the vehicle and Angular rateω_{ib}, the output of these results in GPS data, which is positioned, used to access as input to the filters. While observing the values of the vectors with INS signals.

Fig. 3 and Fig. 4 for predicting the Kalman and $\mathbf{H}_\infty$ in the GPS outage irrespectively.

$\boldsymbol{H_\infty}$ Filter

Firstly, the process of $\mathbf{H}_\infty$ a filter is given below in Fig. 5

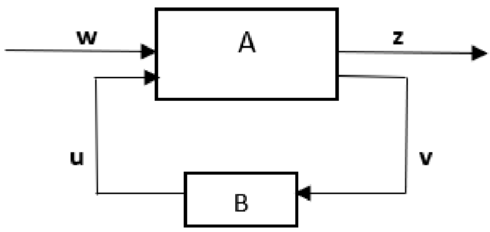

Fig .5 Model of $\mathbf{H}_\infty$ methods in a control circuit

$\mathbf{H}_\infty$ filter consists of a circuit, where A gives two outputs (z) the error signal this has to be reduced to estimate this variable (v) that results in the switch the model. Y is used as an input, (w) serves as an external input, to refer to the signal and (Z) variable while E, F are taken as matrices of Y, Z considering the equation.

$$\begin{bmatrix} F \\ S \end{bmatrix} = G(S) \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} G_{11}(L) G_{12}(L) \\ G_{21}(L) G_{22}(L) \end{bmatrix} \begin{bmatrix} y \\ z \end{bmatrix} \text{-- (1)}$$

$$H = Z(S)u \text{-- (2)}$$

d dependency on was:

$$d = J_l(P,S)y \text{-- (3)}$$

This equation shows the lower fraction value, whereas J_l is given:

$$J_l(G,S) = G_{11} + G_{12}K(1 - G_{22}K)^{-1}G_{21} \text{-- (4)}$$

The transfer function of infinity normalized matrix $J_l(G,S)$ is given:

$$\|J_l(G,S)\|_\infty = \underset{y}{\text{chg}}\, \overline{\omega}\big(J_l(P,S)(xy)\big) \text{-- (5)}$$

Where $\big(J_l(P,S)(xy)\big)$ the max value of the singular matrix is given as $\overline{\omega}$.

Artificial neural network

In the Artificial intelligence embedded model, we have three layers; the input layer fetches the input value as the vectors data that collects the data that is mapped onto this hidden layer, as well the output results in a 2-D vector. In our proposed scheme, a Multi-Layer Perceptron is trained in a parallel framework, which consists of numerous parameters, which have been estimated in a complex manner.

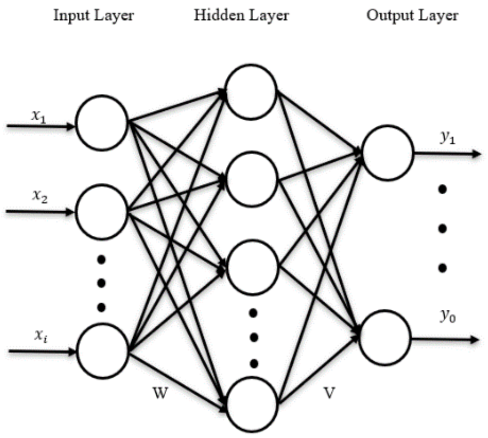

Fig. 6. Multi-layer perceptron framework

Here, the size of the network is considered according to the standard configuration where x is the count of an input layer, y is the count of the output layer, and Uxl: input weight matrix, Syx: output weight matrix.

Neural networks are a standard network in various architectures, the availability to get the precise function, which is non-linear. Fig. 6 consists of three layers in an MLP input layer, hidden layer as well as output layer. The input layer is the count of input in the given network, in this layer, no modifications take place instead, and it just transmits to another layer known as the hidden layer. The hidden layer consists of several layers in addition to this a large count of neurons, which are inactive states because the modifications are done in this layer. The output layer has numerous neural networks, which give the output value, which consists of an active node from one to another node, perhaps no feedback given the information progresses in the forward direction. In Multi-layer Perceptron, the input obtained is considered as the training part for memory storage, the other two layers for testing purposes.

3. RESULTS AND DISCUSSIONS

3.1. **Performance Evaluation**:

In our proposed model here, an advanced Multi-layer perceptron neural network is used. In Fig. 7 and Fig. 8 the covariance factor of position and velocity is considered. Here the p and v is given as the position and velocity along with the three directions, where x-direction indicates the time sample,

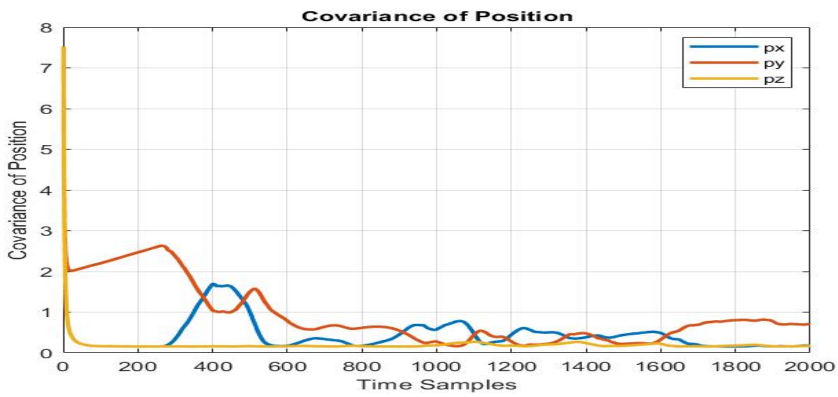

Fig .7. Comparison of covariance along with time samples

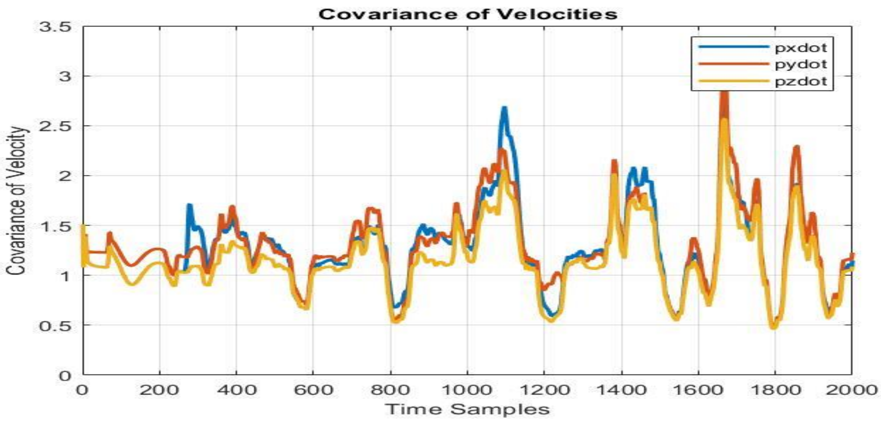

Fig .8. Comparison of covariance of velocities along with time samples

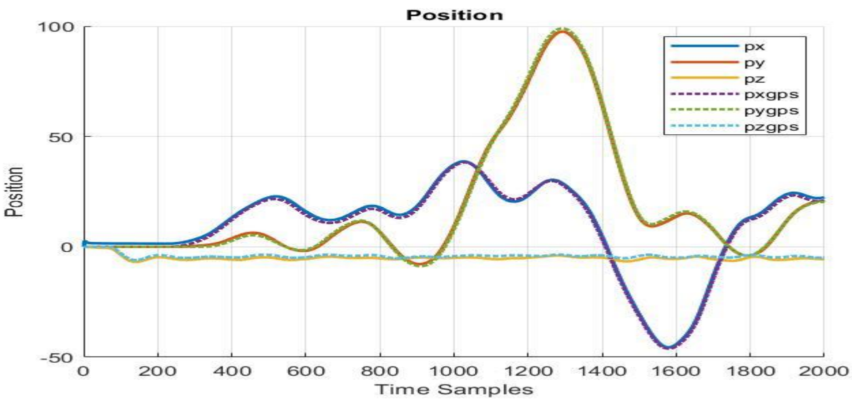

Fig 9. Graph plot of position against time samples

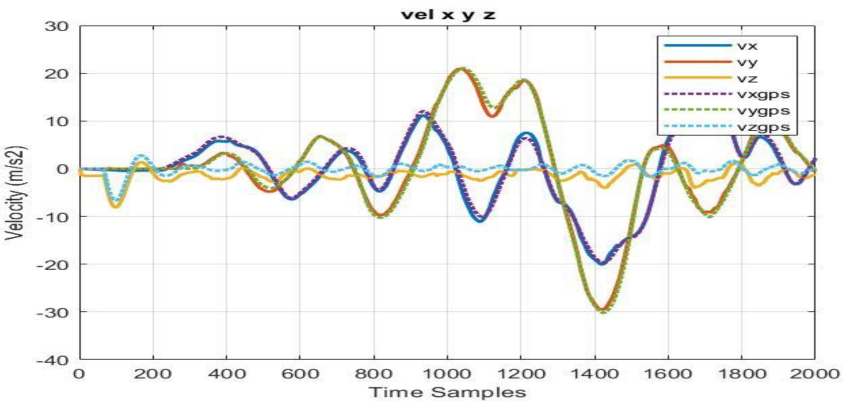

Fig .10. Velocity calculated along x y z

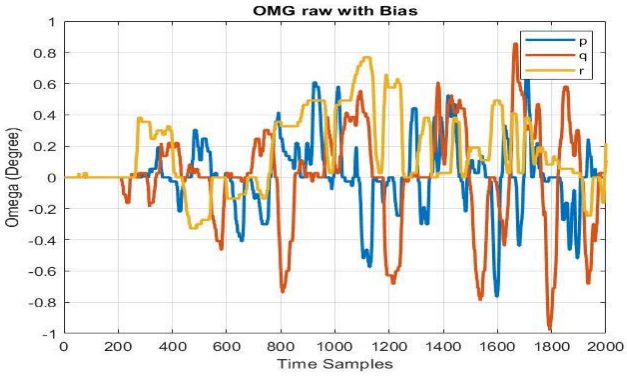

Fig .11. Omega value along with the raw bias

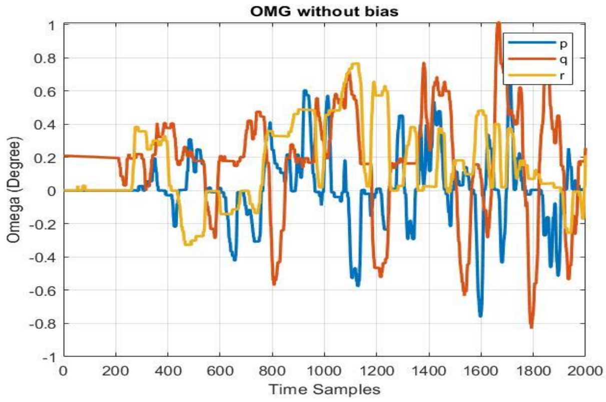

Fig .12. . Omega value without raw bias

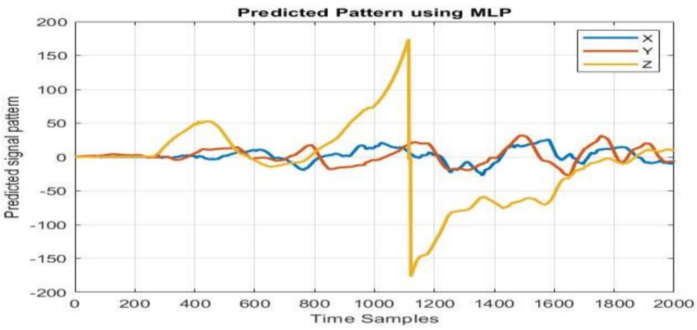

Fig .13.The predicted signal pattern in comparison with predicted pattern from MLP

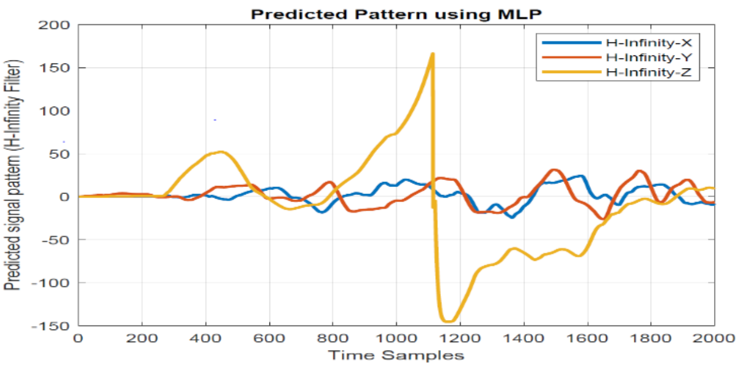

Fig .14. $\mathbf{H}_{\infty}$ filter predicted pattern from MLP

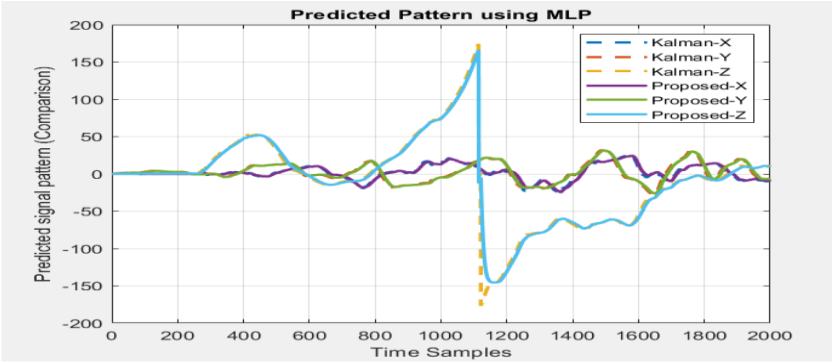

Fig .15. Comparison of $\mathbf{H}_{\infty}$ with Kalman filter

3.2. Comparison Results

Our proposed system here depicts the approximate position within the range of GPS outages. The below table shows, the values compared various GPS outages across time. The (RMSE) value and the signal error value are used for evaluation purposes.

TABLE 1. Comparison of max and RMSE values with $\mathbf{H}_{\infty}$ and Kalman filter

S. No	Original		Kalman Using MLP		H-Infinity Using MLP	
	MAX	RMSE	MAX	RMSE	MAX	RMSE
1	54.17	19.20	28.29	11.46	26.52	10.21
2	57.06	23.94	27.34	12.37	25.23	11.53
3	73.53	30.63	30.86	13.48	28.85	12.55
4	94.82	41.22	44.52	17.21	42.13	16.18

By the results shown in above table, we conclude, our proposed model is works effectively when GPS outages occur. Here the prediction is made on the basis of, $\mathbf{H}_{\infty}$ which performs better in comparison made along the Kalman filter. The estimation of position results in error values for both $\mathbf{H}_{\infty}$ and Kalman filter, while reducing the error it gives an accurate value for the positioning which occurs during GPS outage.

4. Conclusion

Here experimental analysis is carried out on a MATLAB framework for simulation purpose. Comparison of the respective program along with the Kalman and $\mathbf{H}_{\infty}$ filters the comparison of the results shown in the table states that $\mathbf{H}_{\infty}$ performs very well in comparison with the Kalman filter. Position error estimation value for both the filters Kalman filter and $\mathbf{H}_{\infty}$ filter results in less error rate for the Kalman filter. We can conclude by proving that $\mathbf{H}_{\infty}$ the filter has better efficiency in comparison with Kalman filtering following the time taken to perform the entire process. In the future, more research needs to be carried out on the control algorithms, which are used for quality for integrating and performing further tests on real data sets, need to be taken care of.

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