ISSN:0975-9646

Pratibha Singh et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (3) , 2014, 3787-3790

Performance of Kalman Filter on Filtering Colored Noise

Pratibha Singh, Kiran Jain, Shivnandan Singh

Department of Computer Science and Engineering, Galgotias University, Greater Noida (U.P),India

Abstract - This paper gives a core approach to model errors encountered during vehicular tracking using Global Positioning System. The errors occur due to the lateral transference of signals from sending to receiving end which ultimately degrades the efficiency and accuracy of signals. These errors could be in the form of ionospheric delay, multipath effects, delay in trospheric layer, atmospheric distortion etc.GPS uses UTC time to position the navigated device. Here, we have tried to improve the accuracy of GPS positioning by filtering out the distortions in the GPS signals using Kalman Filter. This proposed approach uses prediction and correction for estimating and predicting parametric values using prior, present and future measurements to collect more consistent signal. We showed better precision of filter in this paper by eradicating noise and achieved lesser mean error than standard one.

***Keywords*-GSM,latitude mean error, longitude mean error,noise covariance.**

I. INTRODUCTION TO GPS SYSTEMS

A GPS System uses total of 24 geodic earth monitoring satellites to monitor the position of a unit. The target unit should be in the range of minimum of 4 satellites to compute its exact location. The GPS receiver is used to observe signal that is being transmitted by the satellites.

The ability to detect the vehicle’s current status and location accurately is the main goal of a vehicular tracking system. Tracking units includes the techniques of Global Positioning Systems, Embedded Systems, and Wireless Communication etc.

It should be in the range of minimum of 4 satellites to compute its exact location. The GPS receiver is used to observe signal that is being transmitted by the satellites.

The ability to detect the vehicle’s current status and location accurately is the main goal of a vehicular tracking system. Tracking units includes the techniques of Global Positioning Systems, Embedded Systems, and Wireless Communication etc.

A GPS tracking unit determines the exact position of a vehicle, unit, person, or an asset to which it is attached and records its position at regular intervals. The recorded data is stored within the Unit, or it may be further transmitted to a centralized data base, or within a computer using a cellular (GPRS), GSM modem implanted in the unit.

There are several errors that occur during GPS positioning which degrades system’s accuracy and performance. These sources of distortion can be in the form of ionospheric delays, satellite and receiver clock errors, atmospheric delays, dilution of precision, multipath,delay of signal in troposphere layer, selective availability and anti-spoofing. [4].These errors can be reduced to get a more efficient estimate of the position of the investigated unit.

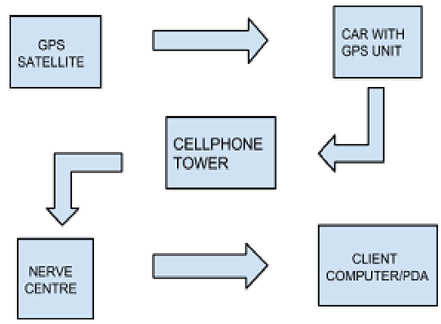

Figure1. Schematic diagram of Global positioning System.

II.SYSTEM OVERVIEW

In this research, we have proposed to track the position of a vehicle by using GPS and GSM technology. We are using GPS tracking Unit which is an embedded application. It regularly monitors a moving vehicle and stores the position of the vehicle on demand. An AT89S52 microcontroller is serially connected to the GSM modem and a GPS receiver. A GSM modem continuously sends the status of the vehicle from a distant place. This data will be in the form of the latitude and longitude with respect to the time signifying the location of the vehicle. The GPS modem gives NMEA data as an output which is further read and displayed on the LCD screen. The same data is send to the mobile from where the status of the vehicle is demanded and the mobile number is stored in an EEPROM .Here we are using RS-232 protocol for the communication between the modem and the microcontroller serially. A driver IC is used for converting TTL voltage levels to RS -232 voltage levels. Whenever the user sends the request to the number at the modem, a return response is sent automatically to that mobile given the position of the vehicle in the terms of latitude and longitude.

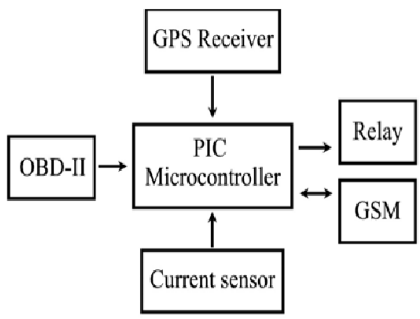

Figure 2: A Vehicular tracking Unit

III. THE KALMAN FILTER

It serves as an important mathematical toolbox for the estimation of current status of a unit from the noisy sensors. It minimizes the mean of squared error. It provides an proficient recursive (computational) means to estimate the state of a process [5]. It reduces the probable *error* Covariance, when some required conditions are met. The unique characteristics of the Kalman filter include the interpretation of its mathematical formulation in terms of state and measurement implementation. The previous estimate must be stored in order to compute the update estimate from the Prior estimated state. This filter acts as a computational algorithm which processes the measurements to reduce the minimum error estimation of the system. It analyzes the current state of the system by measuring the modifying figures of the system, measurement noise measurement errors and preliminary condition information.

The advantages of kalman filter are:

1. It gives the best possible location of the estimation of next frame.
2. It improves the error detection rate of the system.
3. It minimizes the searching time of the next frame; henceforth it reduces the processing time.
4. The variance of the kalman filter is smaller than variance of the other adaptive filters being used in large data sets.
5. It serves as one of the best smoothing algorithm.
6. It deduces the phantom detection rate.

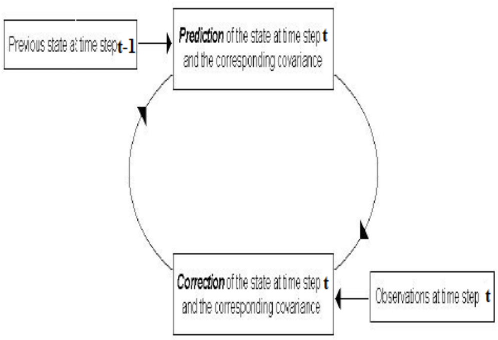

Figure 3. Diagramatic view of Kalman Filter

The equations for the Kalman filter are categorized into two groups which are Prediction and correction. The prediction is responsible for predicting parameter values next to the current state while Correction is responsible for comparing current parameters to the prior parameters.

IV. PROBLEM STATEMENT

The Kalman filter serves as a solution for a general dilemma of estimating the state x ∈ $\Re$n of a distinct time restricted processes. This model assumes that the state of a system at a time t evolved from the prior state at time t-1 is controlled by a linear stochastic differential equation as shown in equation (1):-

$X_t = A_t X_{t-1} + B_t U_t + W_{t-1}$ (1)

Where

A_t is the state of system at an instant of time t;

U_t is the input vector containing control inputs;

F_t is state transition matrix in which parameters of a state at time'ť' depends on the parameters of previous state at time 't-1';

B_t is control input matrix whose parameters depend on the input vector U_t;

W_{t-1} is vector containing process noise.

In equation (1), the differential matrix A signifies the previous time step t-1 to current time step t in the absence of process noise.

Measurement equation in system is as follows:

$Z_t = H_t X_t + V_t$ (2)

Where;

Z_t is the vector of measurement matrix;

H_t is the transformation matrix which maps the state vector parameters into the measurement domain;

V_t is measurement noise in terms of measurement vector;

The measurement noise V_t and the process noise W_t is assumed to be zero mean Gaussian white noise with covariance R_t. Process noise is assumed to be derived from Normal Distribution with covariance matrix Q

$P(W) \sim N(0,Q)$ (3)

$P(V) \sim N(0, R)$ (4)

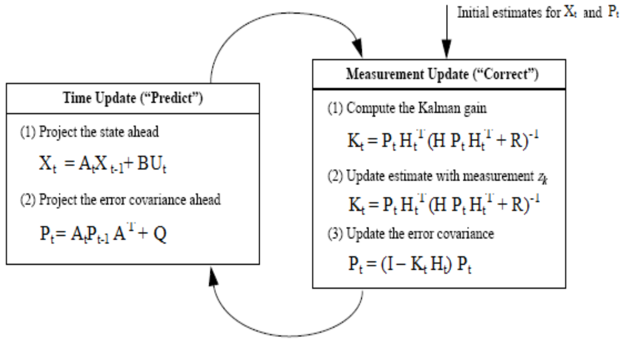

Figure 4.Operations performed in Kalman Filter

The process noise covariance matrix'Q' and measurement noise covariance matrix'R' in the equations (3) & (4) can vary with each other.

Here, we have assumed that they are constant. [5] (Peter S My beck (2001).

The time update equations are used to estimate the next state by extrapolating the present state and error covariance to get the *priori* estimates.

The measurement update equations adjust the probable estimate by actual measurement at that particular time and are used to get the feedback.

Time Update equation and measurement Update equation of the Filter are:

Discrete kalman filter time update equations (5 &6) are given as –

$X_t = A_t X_{t-1} + BU_t$ (5)

$P_t = A_t P_{t-1} A^T + Q$ (6)

Discrete kalman filter measurement update equations (7, 8& 9) are given below.-

$K_t = P_t H_t^T (H P_t H_t^T + R)^{-1}$ (7)

$X_t = Xt + K_t (Zt - H_t X_t)$ (8)

$P_t = (I - K_t H_t) P_t$ (9)

The time update equations serves as the predictor equations while the measurement update equations as corrector equations. In fact, the vary estimation algorithm resembles like predictor-corrector algorithm for solving mathematical problems

V. Parameters And Tuning Of Filter

The initially the Kalman gain K_t is computed during the measurement update. Secondly, the process vector Z_t is measured to obtain an *a posteriori* state estimate by calculating the measurement as in equation (8).Finally *a posteriori* error covariance estimate is generated as in equation (9). After each prediction and correction pair, the process is frequently repeated, with the previous *a posteriori* estimates. Henceforth, Kalman Filter works recursively which makes it more practical and feasible than the other filters (for ex- Wiener filter, Butterworth filter).It is designed to work on all of the datasets openly for each estimate. The modifications are generally performed off-line, repeatedly with the help of different Kalman filter in a process usually termed as *system identification.*

Lastly, we note that under conditions where the process noise covariance matrix (Q) and measurement noise covariance matrix(R) are constant, so the estimation error covariance and the Kalman gain will become constant rapidly. However, the measurement error particularly varies in some cases. The process noise sometimes changes during filter operations in order to adjust to different dynamics.

- When the error covariance (R) approaches zero, the actual measurement (Z_t) is trusted more but the predicted measurement (X_t) is trusted less.
- When a priori estimate error covariance approaches zero, the actual measurement (Z_t) is trusted less but the predicted measurement (X_t) is trusted more.

VI.Results And Discussion

We have used a single frequency ML 300 GPS hand held Receiver and collected the data at different locations around Delhi, Noida and Meerut. We have shown how the data set been collected in terms of Longitude, Latitude and Altitude is passed through the Kalman filter. We have calculated the variance mean error of the data set when passed through Kalman filter. Improvement in the performance of system is encountered by filtering out irregularities such as noise and distortion level. This filtration technique increases the efficiency and performance level of the system making it more consistent as compared with other conventional vehicle tracking system. As calculated, the latitude mean error is 0.02484, longitude mean error is 0.005087 and altitude mean error is 0.0047282, which is reduced by using Kalman filter. These results are very efficient as compared with previously compared results.

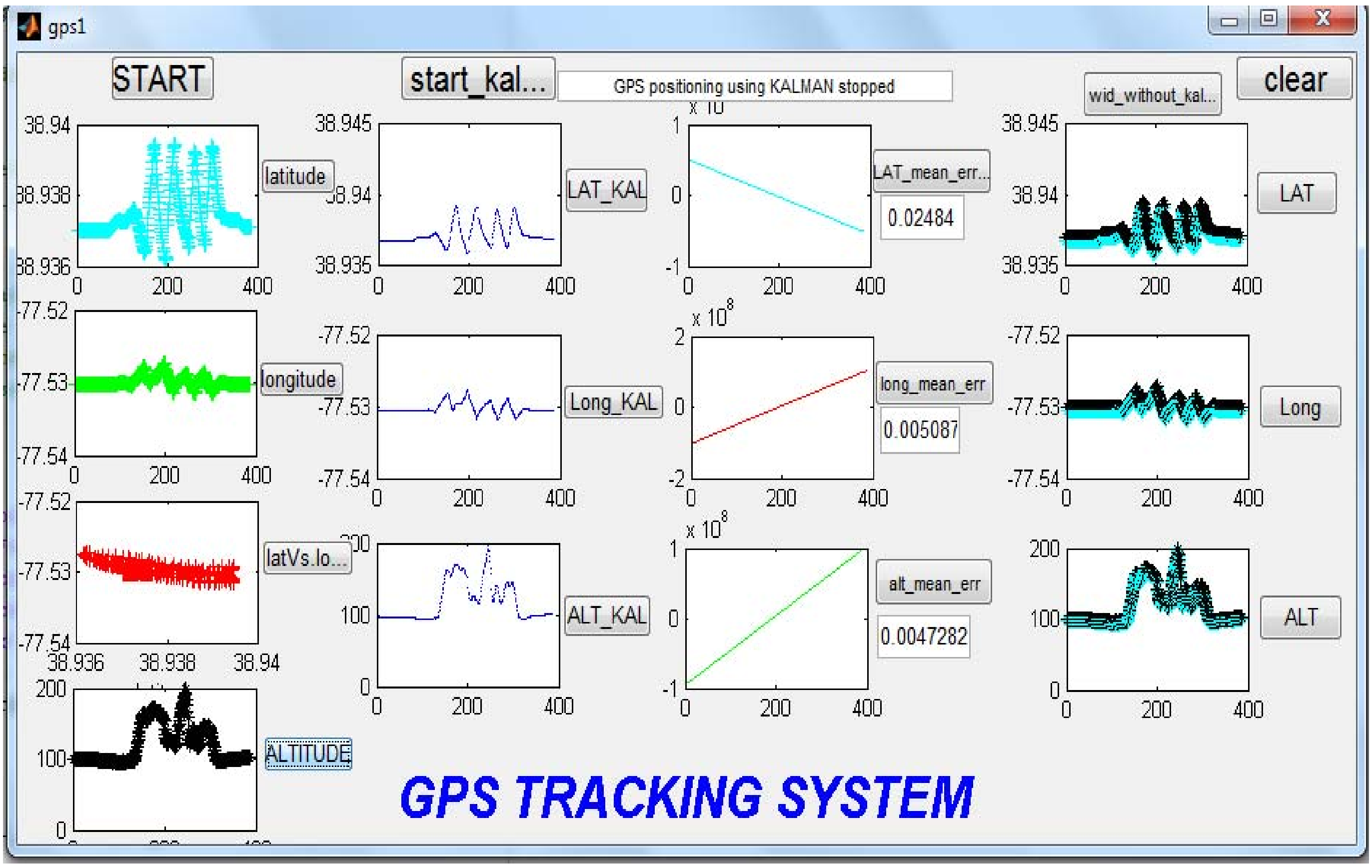

Figure 5. Signals passing with and without Kalman Filter

VII. CONCLUSION

In this paper, we have gathered data from different locations. This data is plotted in the form of graph which shows larger amount of fluctuations in the signals due to noise co-variance. GPS signals has certain drawbacks which causes distortions in the form of color noise, Gaussian noise, heat, white noise, light which are being removed by applying kalman filter.

The data is passed through Kalman Filter for the prediction of most probable location of the vehicle to yield better results. It gives the accurate estimation of the location. However the implementation of this application is being used for the smoothening of the image or signal being processed.

REFRENCES

[1] Grewal, Mohinder S., and Angus P. Andrews. "Kalman Filter: Theory and Practice Using MATLAB." *Wieley-Interscience, Canada* (2001).

[2] Malleswaria, B. L., et al. "PERFORMANCE OF KALMAN FILTER FOR GPS DATUM CONVERSION."

[3] Parkinson, Bradford W., and James J. Spilker, eds. *Global Positioning System: part 1 GPS fundamentals, part 2 GPS performance and error effects; vol. 2, part 3 differential GPS and integrity monitoring, part 4 integrated navigation systems, part 5 GPS navigation applications, part 6 special applications*. Vol. 2. Aiaa, 1996.

[4] Malleswari, B. L., et al. "THE ROLE OF KALMAN FILTER IN THE MODELLING OF GPS ERRORS." *Journal of Theoretical & Applied Information Technology*5.1 (2009).

[5] Bishop, Gary, and Greg Welch. "An introduction to the kalman filter." *ProcOf SIGGRAPH, Course* 8 (2001): 27599-3175.

[6] Maybeck, Peter S. *Stochastic models, estimation, and control*. Vol. 3. Academic press, 1982.

[7] Julier, Simon J., and Jeffrey K. Uhlmann. "Unscented filtering and nonlinear estimation." *Proceedings of the IEEE* 92.3 (2004): 401-422.

[8] MacCormick, John, and Andrew Blake. "A probabilistic exclusion principle for tracking multiple objects." *International Journal of Computer Vision* 39.1 (2000): 57-71.

[9] Mohamed, A. H., and K. P. Schwarz. "Adaptive Kalman filtering for INS/GPS."*Journal of Geodesy* 73.4 (1999): 193-203.

[10] Qi, Honghui, and John B. Moore. "Direct Kalman filtering approach for GPS/INS integration." *Aerospace and Electronic Systems, IEEE Transactions on* 38.2 (2002):

[11] Hide, Christopher, Terry Moore, and Martin Smith. "Adaptive Kalman filtering for low-cost INS/GPS." *The Journal of Navigation* 56.01 (2003): 143-152

[12] Qi, Honghui, and John B. Moore. "Direct Kalman filtering approach for GPS/INS itegration." *Aerospace and Electronic Systems, IEEE Transactions on* 38.2 (2002):687-693.