THE ROLE OF KALMAN FILTER IN IMPROVING THE ACCURACY OF GPS KINEMATIC TECHNIQUE

Dr. Tarek Abd El-Hamied Hassen El-Damaty
Faculty of Engineering, Banha Universit, Egypt

ABSTRACT

This paper focuses on the estimation of the receiver coordinates (x, y) of a set of points based on pseudo range measurements of a single GPS receiver. The errors that affecting the GPS signal are degrading the accuracy of GPS position. Kalman filter is used to improve the accuracy of kinematic GPS point positioning using a single frequency I-COM GP 22 hand held receiver that obtained the coordinates along a part (30 km) of Cairo – Suez highway. A Kalman filter has the capability to characterize the noise sources in order to minimize their effect on the desired receiver output. The heart of the GPS-Kalman filter is an assumed model of how its state vector changes in time. The state vector contains the parameters describing the model and includes at least the receiver position (x, y). Kalman filter is a recursive estimator that produces the minimum covariance estimate of the state vector. Kalman filter sorts out information and weights the relative contributions of measurements compared with its assumed model. The proposed Kalman model was applied on the study area of Cairo –Suez highway. The results of proposed Kalman filter model give better accuracy with more consistency. Kalman filter technique is as an important tool for any dynamic process.

Keywords: GPS – Kalman filter – errors - accuracy

I. INTRODUCTION

A Satellite-based system Global Positioning System uses a constellation of 24 satellites to give an accurate position of user. GPS receivers have been developed to observe signals transmitted by the satellites and achieve sub meter accuracy in point positioning and a few centimeters in relative positioning. GPS can be operated in all weather; day and night without any requirement of inter visibility between points. GPS provides a global absolute positioning capability with respect to a consistent terrestrial reference frame and considered as an absolute global geodetic positioning system. The GPS satellites are positioned in such a way that at least five to eight satellites are accessible at any point on earth and at any time (Hoffmann-Wellonhaff et al, 1998).
There are several sources of error that degrade the GPS position from few meters to tens of meters (Pratap Misra, 2001). These error sources are Ionospheric, Atmospheric delays, Satellite and Receiver Clock Errors, Multipath, Dilution of Precision, Selective Availability (S/A) and Anti Spoofing (A-S) as described by Hoffmann - Wellenhof et al (1998). The errors could be transmitted via VHF/UHF links and the users can make use of the corrections to fix their positions more accurately. These errors can be reduced to arrive at a more accurate estimate of coordinates of user by means of a recursive algorithm- KALMAN FILTER. The emphasis is given on the above errors to analyze the Kalman filter (Grewel.M. S et al, 2001).

II. Kalman Filter Principles

The general stochastic filtering problem is to recursively estimate the current state of a random process through an observation process. Kalman filter, as a recursive estimate method, has come to be widely used in geodetic and surveying practice for the last decades. This method solves the estimation problem for a linear dynamic system with noisy observation (Wang and Kubik, 1990).

Kinematic Model
The kinematic model is applied to describe the motion of the vehicle and the dynamic noise associated with such motion (Gao, and Krakiwsky, 1992). The following first order differential equation is representing the dynamics of the linear system:

\[ X'(t) = F(t) + W(t) \quad (1) \]

Where \( X(t) \) is the system state vector that contains all parameters, \( F(t) \) is the dynamic matrix and \( W(t) \) is the random forcing matrix.

Linearized Equations
The explanation of the build up of the linearized equations in terms of one cycle of Kalman filter loop will be presented. The corresponding linearized dynamic model of equation (1) described by the following relations:

\[ X_{h+1} = \phi_h + W_h \quad (2) \]

The observations (measurements) of the process is assumed to occur at discrete points in time accordance with the linear relationship:

\[ Z_h = H_h X_h + V_h \quad (3) \]

Where \( X_h \) is the process state vector at time \( t \), \( \phi \) is a matrix relating \( x(t) \) to \( x(t+1) \), \( W_h \) is a vector assumed to be a white (uncorrelated) sequence with known covariance structure, \( Z_h \) is the measurement vector at time \( t \), \( H_h \) is a matrix giving the ideal (noiseless) relation between the measurements and the state vector at time \( t \) and \( V_h \) is the measurement errors, assumed to be a white sequence with known covariance structure and uncorrelated \( W_h \) with sequence. The covariance matrices of \( W_h \) and \( V_h \) vector are given by:
E[ \mathbf{W}_h \mathbf{V}_i^T ] = Q_h \text{ only at } i=h \quad (4)

E[ \mathbf{V}_h \mathbf{V}_i^T ] = R_h \text{ only at } i=h \quad (5)

E[ \mathbf{W}_h \mathbf{V}_i^T ] = 0 \text{ for all } h \text{ and } i \quad (6)

We assume at this point that we have an initial estimate (prior estimate \( \mathbf{X}_{h-} \)) of the process at specific time \( t_h \). We also assume that we know the error covariance matrix (\( \mathbf{P}_{h-} \)) associated with the prior estimate. In many cases, the estimation problem is started with no prior measurements. Thus, in this case, the process mean is zero, the initial estimate is zero and the associated error covariance matrix is just the covariance matrix of \( \mathbf{X} \) itself (Brown R.G., 1983). With the assumption of a prior estimate \( \mathbf{X}_{h-} \), the \( Z_h \) measurements are used to improve the prior estimate according to the following equation:

\[
\mathbf{X}_{h+} = \mathbf{X}_{h-} + \mathbf{K}_h (\mathbf{Z}_h - \mathbf{H}_h \mathbf{X}_{h-}) \quad (7)
\]

Where \( \mathbf{X}_{h+} \) is the update estimate and \( \mathbf{K}_h \) is the blending factor, which minimize the mean square error and it called the Kalman gain. The state after measurement incorporation is generally accepted as the most optimal state in the filter since it is punctual and has the most recent measurement.

After the measurement is incorporated, the next step is to update the covariance for the next state update; therefore the covariance matrix associated with the optimal estimate can be compute from this equation:

\[
\mathbf{P}_h = (\mathbf{I} - \mathbf{K}_h \mathbf{H}_h) \mathbf{P}_{h-} \quad (8)
\]

In this equation, \( \mathbf{I} \) is the identity matrix and Kalman gain determine the amount by which the covariance has been improved by the new measurement. The Kalman gain is the results of a calculation performed at each measurement update time, based on the propagated covariance from the previous time \( \mathbf{P}_{h-} \) and the measurement noise covariance \( \mathbf{R}_h \). The Kalman gain can be computed from the following equation:

\[
\mathbf{K}_h = \mathbf{P}_{h-} \mathbf{H}_h^T / (\mathbf{H}_h \mathbf{P}_{h-} \mathbf{H}_h^T + \mathbf{R}_h) \quad (9)
\]

Although this equation seems complex, a simple assumption will develop an intuitive understanding for this gain calculation. Assume that the state and measurement are in the same coordinate form (so \( \mathbf{H}_h \) is the identity matrix) and the Kalman gain will be:

\[
\mathbf{K}_h = \mathbf{P}_{h-} / (\mathbf{P}_{h-} + \mathbf{R}_h) \quad (10)
\]

For large uncertainty in the state model \( \mathbf{P}_{h-} \) compared with the uncertainty in the measurement noise model \( \mathbf{R}_h \), Kalman gain applied to the new measurement is near unity. Finally, the update \( \mathbf{X}_{h+} \) is easily projected ahead via the transition matrix through the next equation:

\[
\mathbf{X}_{(h+1)+} = \phi_h \mathbf{X}_{h+} + \mathbf{W}_h \quad (11)
\]

We have to notice here that equal to zero in case of constant speed.
Kalman Filter Loop

The loop of Kalman filter model could be clear through the following figure. It should be clear that once the loop is entered, it could be continued to infinity.

Enter prior estimate and its error covariance

\[(X_{h-}, P_{h-})\]

Compute Kalman gain

\[K_h = P_{h-}H_h^T / (H_h P_{h-} H_h^T + R_h)\]

Update estimate with measurement

\[X_{h+} = X_{h-} + K_h (Z_h - H_h X_{h-})\]

Compute error covariance for updated estimate

\[P_h = (I - K_h H_h) P_{h-}\]

III. Material and Methods

The main objective of this study was to explore the feasibility of integrate the proposed Kalman filter model with GPS observations in order to improve the position accuracy. The study took place along Cairo – Suez highway. A 30 km stretch of the road path was selected. The receiver was equipped in small car; which moved with constant speed approximately. During moving along the selected path the position of pre-selected points and the car velocity was determined using GPS receiver.

The equipment included a small car with a GPS receiver on board. The GPS receiver was a five channel one and its model is I-COM GP-22. The manufacture specification of the receiver gives an accuracy of +/- 15 m at the absence of signal interruption. The receiver was observing continuously and the position was determined every 30 sec. The obtained coordinates were Cartesian (east, north) in WGS 84 system. It is worth mentioning that no significant obstructions or signal interruption occurred.

The obtained observations were prepared and entered to the proposed Kalman filter model to get the filtered position coordinates. The path of the study highway was plotted before and after filtering and compared to each other graphically and then each one was compared to the actual path that digitized from a map with scale 1:5000.
IV. RESULTS AND DISCUSSION

The coordinates (easting and northing) were obtained along the highway path of the right traffic lane in direction from Cairo to Suez; obtained in WGS 84 reference datum. The datum of the reference map was also WGS 84 and its projection was Universal Transverse Mercator (UTM). Table (1) presents the following data:

(a) A sample of GPS node coordinates (before filtering).
(b) A sample GPS node coordinates after filtering through the proposed Kalman filter model within a software module.
(c) The same set of coordinates that obtained from the referenced map with scale 1:5000.

Table (1): A GPS node coordinates

<table>
<thead>
<tr>
<th>Point ID</th>
<th>Coordinates before filtering</th>
<th>Coordinates after filtering</th>
<th>Map coordinates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>East (m)</td>
<td>North (m)</td>
<td>East (m)</td>
</tr>
<tr>
<td>P1</td>
<td>660783</td>
<td>828110</td>
<td>660783</td>
</tr>
<tr>
<td>P2</td>
<td>660890</td>
<td>828110</td>
<td>660862</td>
</tr>
<tr>
<td>P3</td>
<td>660970</td>
<td>828110</td>
<td>661031</td>
</tr>
<tr>
<td>P4</td>
<td>661104</td>
<td>828203</td>
<td>661178</td>
</tr>
<tr>
<td>P5</td>
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<td>828958</td>
<td>664944</td>
</tr>
</tbody>
</table>

The two paths (before and after filtering) were compared against actual path obtained from the referenced map as shown in figure (2) and (3).
Figure (2): The path before filtering and the path from the reference map

Figure (3): The path after filtering and the path from the reference map

Due to the low sample rates (respectively), some of the significant geometric features of the road were not accurately mapped. The sampling rate in GPS could be a source for errors in terms of geometric characteristics of the path. Other potential sources of errors included the conventional sources such as atmospheric effect, orbit accuracy, pseudo range...
resolution and dynamic effect. In addition, the digitizing process of the path from the original map is another source of error. The errors in easting and northing direction ($\Delta E$ and $\Delta N$) were determined for all points before and after filtering by subtracting the coordinates of observation points before and after filtering from the coordinates of reference map. Table (2) presents the error values.

<table>
<thead>
<tr>
<th>Point ID</th>
<th>$\Delta E_b$ (m)</th>
<th>$\Delta N_b$ (m)</th>
<th>$\Delta E_a$ (m)</th>
<th>$\Delta N_a$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>P2</td>
<td>-38</td>
<td>5</td>
<td>-10</td>
<td>5</td>
</tr>
<tr>
<td>P3</td>
<td>56</td>
<td>48</td>
<td>-5</td>
<td>-8</td>
</tr>
<tr>
<td>P4</td>
<td>70</td>
<td>25</td>
<td>-4</td>
<td>-9</td>
</tr>
<tr>
<td>P5</td>
<td>22</td>
<td>-13</td>
<td>2</td>
<td>4</td>
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<tr>
<td>P6</td>
<td>2</td>
<td>-39</td>
<td>0</td>
<td>0</td>
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<tr>
<td>P7</td>
<td>94</td>
<td>-8</td>
<td>-6</td>
<td>-7</td>
</tr>
<tr>
<td>P8</td>
<td>26</td>
<td>4</td>
<td>-5</td>
<td>-4</td>
</tr>
<tr>
<td>P9</td>
<td>75</td>
<td>11</td>
<td>2</td>
<td>-2</td>
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<td>1</td>
<td>11</td>
</tr>
<tr>
<td>P11</td>
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<td>0</td>
<td>2</td>
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<tr>
<td>P12</td>
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<td>-4</td>
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<td>0</td>
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<tr>
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<td>-3</td>
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<tr>
<td>P14</td>
<td>-14</td>
<td>4</td>
<td>-4</td>
<td>-2</td>
</tr>
</tbody>
</table>

The numerical results of error analysis for all observed data were on the order of 28 m (RMS) before filtering and decreased to 12 m (RMS) after filtering. Figure (4) and (5) show the errors in east and north direction before and after the filtering the data sample. It is clear that the errors in both easting and northing direction was decreased after filtration; which means the Kalman filter model has improved the accuracy of GPS kinematic observations.

Figure (4): The errors in east direction before and after filtering

Figure (5): The errors in north direction before and after filtering
Figure (5): The errors in north direction before and after filtering

V. CONCLUSION

Based on the Kalman filter concept overview, GPS kinematic procedures and the points investigated in this paper through the experiment, a number of conclusions can be summarized as follows:

1- It is clear that Kalman filter has a significant effect in improving the accuracy of GPS observations in kinematic positioning technique and certainly yields to better results.

2- GPS kinematic measurement is corrupted by noise, which introduces errors in calculations. This noise includes errors in the ionospheric corrections and system dynamics not considered during the measurement process. Kalman filter technique has the capability to have noise source characterized in order to minimize their effect on the desired measurements.

3- The GPS absolute kinematic mode could be used to update maps with scale 1:15000 or smaller. Also it may used to establish special purpose maps, which not need high accuracy such as tourists guide and emergency map.

Future research will be directed to develop and examine a fuzzy extended Kalman filter. Also further works can focus on how to improve the initial values of the filter and the covariance matrices.

REFERENCES

3. Gao, Y. and Krakiwsky E. (2001), Experience with the application of federated filter design to kinematic GPS positioning, Department of surveying engineering, Calgary university, Calgary, Canada.


8. Wang, Y. and Kubik,K. (1990), Robust Kalman filter for GPS real time positioning School of surveying, Queen’s land university of technology, Brise bane, Australia.

9. Ravi Kumar Jatoth and Dr.T.Kishore Kumar, “Real Time Implementation of Unscented Kalman Filter for Target Tracking” International Journal of Electronics and Communication Engineering & Technology (IJECET), Volume 4, Issue 1, 2013, pp. 208 - 215, ISSN Print: 0976- 6464, ISSN Online: 0976 – 6472, Published by IAEME.

AUTHORS' INFORMATION

Tarek A. El-Damaty received B.Sc. from the faculty of engineering, Ain Shams University, Egypt, the M.Sc. degree from the faculty of engineering, Banha university, Egypt and Ph.D. degree from faculty of civil engineering, technical university in Prague; CZ. He is currently working as an Assistant Professor in College of Engineering and Islamic Architecture, Umm Al_Qura University, K.S.A. His research interests include GPS, GIS, Remote sensing and decision-support system.