Integration of GPS/INS Navigation System with Application of Fuzzy Corrections

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Abstract

The integration of GPS/ INS based on Artificial Intelligence is presented.The data from GPS and Inertial Navigation System (INS) are used to construct a structured knowledge base consisting of behavior of INS in some special scenarios of vehicle motion. With the same data, the proposed fuzzy system is made to obtain the corrected navigation data. In the absence of GPS information, the system will perform its task only with the data from INS and fuzzy correction algorithm using Matlab/Simulink.

Keywords: INS, Fuzzy System, Kalman Filter, Membership Function.

1. Introduction

The vulnerabilities of GPS are related to intentional disruption of the service, asinvoked in [1], to the loss of accuracy in thenarrow-street environment [2], due to a poorgeometrical-dilution-of-precision (GDOP) coefficient and to the multipath reflection. The presence of noisein GPS signals compels the use of narrow bandwidth filters, which limits the dynamic of the vehicle [3]. Being a satellite navigation system, either GPS or GNSS, is not autonomous, it is suitable to integratethis type of navigation system with a different system, which should procure a greater autonomy. Thus the inertial navigation system (INS) is ideal from thispoint of view. In opposition with receiving signals fromsatellites, in the case of GPS, the autonomy of INS is provided by the functioning principle, which is based on measurements of inertia of the vehicle, linearaccelerations, and angular velocities. Theuse of this integration process implies that a smalluncertainty in measurement bias becomes a positionerror that grows with time [4].INS provides self-contained independent meansfor three-dimensional positioning with high short-termaccuracy [5], [6]. The INS accuracy degrades over time,because of the positioning errors caused bythe uncompensated gyro and accelerometer errorsaffecting the INS measurements.INS provideshigh-accuracy three-dimensional positioning whenthe GPS positioning is poor or unavailable over shortperiods of time (e.g., because of poor satellite geometry,high electromagnetic interference, high multipathenvironments, or obstructed satellite signals). In addition, the INS system provides much higher update positioning rates compared with the output rateconventionally available from GPS. Integration of GPS with INSlimits the positioning errors of the inertial systemwith the uniform positioning errors affecting the GPSsystem. These errors depend on the systematic andrandom errors affecting the GPS measurements, asamplified by the satellite geometry. Using the GPSpositions, the GPS/INS integration filter can estimatethe error states affecting the INS measurements. Theseerror state estimates are used to calibrate the INSsystem on a continuous basis. The high accuracyof the INS system over short periods of time allows correction of undetected cycle-slips affecting the GPSmeasurements.

There are two basic GPS/INS integration schemes: loosely (or cascaded or modular) and tightly coupled mode [7]. In the loosely coupled mode, the GPSreceiver and the INS are treated as separate navigationsystems. The GPS receiver contains a filter, whichprocesses the raw GPS observables and suppliesa position, velocity, and time solution. The INSimplement its navigation/attitude algorithms to give aposition, velocity, and attitude. An integrated Kalmanfilter (KF) is then applied to combine the GPS and INS solutions. In the tightly coupled mode, however,only a single KF is applied to process both sets ofsensor data: raw GPS code/phase observations and INS measurements.

The integration between GPS and INS exploitstheir synergy in various approaches, based on the useof KF, with the goal to mitigate the short time errorof GPS and longtime error of INS [8], [9]. Theresulting plant is a combined navigation system thathas better performances than GPS or INS, consideredas stand-alone navigation systems. It should be underlined that in order to calculate the estimate of INS error,KF constantly needs information from both sources: INS and GPS. Based on INS autonomy, we assumethat it will be always available to provide KF withdata. On the other hand, the normal performanceof GPS can be disrupted [1], in such case the accuracy of integrated navigation system will decayto stand-alone INS accuracy. Some attempts to usefuzzy logic in navigation were made to analyze the errors and the flexibility of the system. The role of fuzzy subsystem is to correct the errors of stand-alone INS, taking into account the information stored, built and trained during the availability of the reference source. We have to mention that the output of reference system(that can be GPS or GPS/INS KF integrated system)is used to provide navigational data as long as these are available.

2. TheInference Rules

The proposed input membership function is shown in Fig. 2. For each variable, the inference rules, stored in fuzzy associative memory (FAM), are as follows.

1. If (input variable is negative) then (output is high) (1).
2. If (input variable is zero) then (output is low) (1).
3. If (input variable is positive) then (output is high) (1).

3. Kalman Filter

The Kalman filter is a tool that can estimate the variables of a wide range of processes. In mathematical terms we would say that a Kalman filter estimates the states of a linear system. The Kalman filter not only works well in practice, but it is theoretically attractive because it can be shown that of all possible filters, it is the one that minimizes the variance of the estimation error. Kalman filter is a set of mathematical equation that provides an efficient computational means to estimate the state of a process, in a way that minimizes the mean of the squared error. The filter supports estimation of past, present and future states. It addresses the general problem of trying to estimate, the state of a process that is governed by the linear stochastic difference equation

$$X_{k+1} = AX_k + Bu_k + N_p$$

With measurement

$$Z_{k+1} = HX_k + N_e$$

The random variables N_p and N_e represent the process and measurement noise, they are assumed to be independent with normal probability distributions.

$$P(W) = N(0, Q)$$
$$P(V) = N(0, R)$$

If $\hat{x}_k^-$ is the a priori estimate of the process at time t_k, then the error covariance matrix is defined as

$$e_k^- = x_k - \hat{x}_k^-$$

$$P_k^- = E(e_k^- e_k^T)$$

The matrix n x m K is chosen to be the gain or blending factor that minimizes the aposteriori error covariance. Kalman filter gain is given by

$$K_{k+1} = AP_kH^T(HP_kH^T + N_e)^{-1}$$

Estimation error covariance is given by

$$P_{k+1} = AP_kA^T + N_p - AP_kH^TN_e^{-1} + HP_kA^T$$

Update state estimate

$$x\hat{}_{k+1} = x\hat{}_k + K_k(z_k - H_kx\hat{}_{k+1})$$

3.1 Steps in Kalman Filter

- Compute the derivative of the covariance matrix
  Pxdot =A*Px+Px*transpose(A)+Q
- Update the covariance matrix
  Px=Px+Pxdot*t
- Calculate the derivative of the predicted value of the accelerometer
  - ✓ $\dot{F}1 = -g(\omega z * C2 - \omega y * C3)$
  - ✓ $F1\,\dot{a}ctual = \dot{F}1 + \dot{F}1error$
  - ✓ $F1predicted = F1previous + F1\,\dot{a}ctual * t$
  - ✓ Error= $F1predicted - F1measured F1measured = measured\ value\ from\ accelerometer$
- Compute the error estimate for kalman filter
  E=C*Px*transpose(C)+Rx
- Compute the kalman filter gain
  K=Px*C*inv(E)
- Update the covariance matrix
  Px=Px-Kx*C*Px
- Update the state estimate
  X=X+Kx*Error

Error is a measurement of the difference in the measured state and the estimate state. In our case, it is just the difference between the two accelerometer measured angle and our estimated angle. The above mentioned steps are repeated in a loop till the value of f1 stops changing.
Similarly two separate loops for y axis and z axis must be evaluated to get the correct values using kalman filter.

Kalman Filter X-axis Loop

- Pxdot=A*Px+Px*transpose(A)+Q
- Px=Px+Pxdot*t
- $\dot{F}1 = -g(\omega z * C2 - \omega y * C3)$
- $F1\,\dot{a}ctual = \dot{F}1 + \dot{F}1error$
- $F1predicted = F1previous + F1\,\dot{a}ctual * t$
- Error= $F1predicted - F1measured$
- $F1measured = measured\ value\ from\ accelerometer$
- E=C*Px*transpose(C)+Rx
- K=Px*C*inv(E)
- Px=Px-Kx*C*Px
- X=X+Kx*Error
- $\dot{F}1error = X[0][0]$

Kalman Filter Y-axis Loop

- Pydot=A*Py+Py*transpose(A)+Q
- Py=Py+Pydot*t
- $\dot{F}2 = -g(\omega x * C3 - \omega 2 * C1)$
- $F2\,\dot{a}ctual = \dot{F}2 + \dot{F}2error$
- $F2predicted = F2previous + F2\,\dot{a}ctual * t$
- Error= $F2predicted - F2measured$
- $F2measured = measuredvaluefromaccelerometer$
- E=C*Py*transpose(C)+Ry
- K=Py*C*inv(E)
- Py=Py-Ky*C*Py
- Y=Y+Ky*Error
- $\dot{F}2error = Y[0][0]$

Kalman Filter Z-axis Loop

- Pzdot=A*Pz+Pz*transpose(A)+Q
- Pz=Pz+Pzdot*t
- $\dot{F}3 = -g(\omega y * C1 - \omega x * C2)$
- $F3\dot{a}ctual = \dot{F}3 + \dot{F}3error$
- $F3predicted = F3previous + F3\,\dot{a}ctual * t$
- Error= $F3predicted - F3measured$
- $F3measured = measuredvaluefromaccelerometer$
- E=C*Pz*transpose(C)+Rz
- K=Pz*C*inv(E)
- Pz=Pz-Kz*C*Pz
- Z=Z+Kz*Error
- $\dot{F}2error = Y[0][0]$

4. Illustrations and Photographs

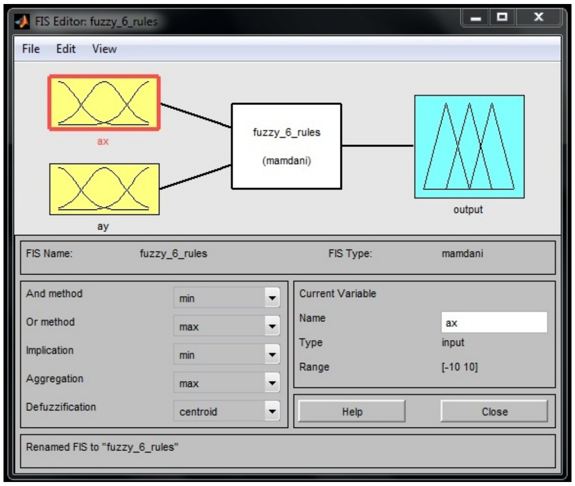

Figure 1. Fuzzy Logic Controller

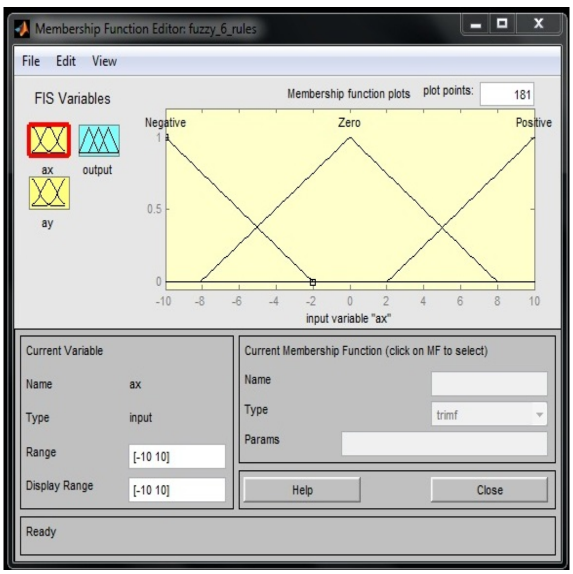

Figure 2. Membership Function

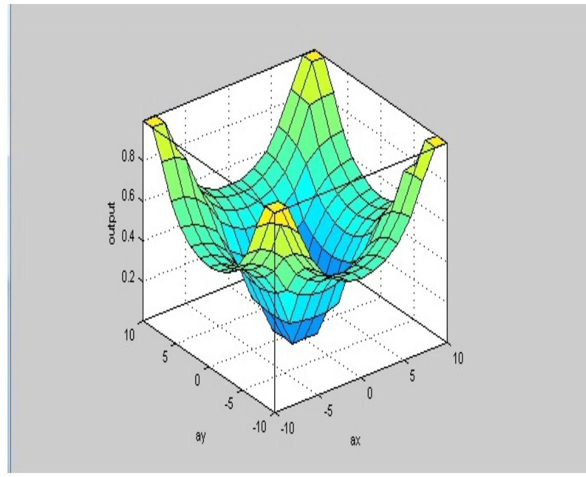

Figure 3. Surface Viewer

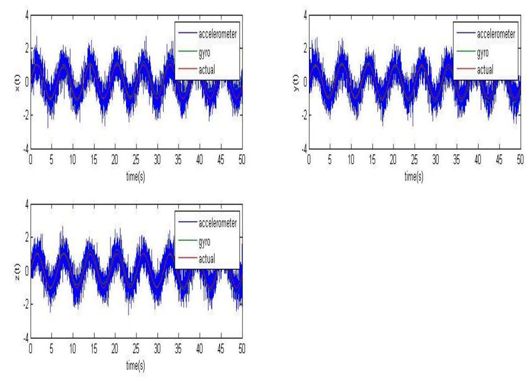

Figure 4.Actual values of accelerometer and gyroscope with the errors

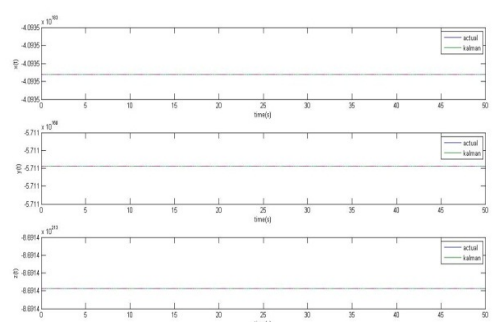

Figure 5. Values of the nth iteration where the error is reduced to the maximum extent

5. Results

The following is the simulation for the error minimization in accelerometer and gyroscope outputs using kalman filter.

Iteration n^{th} Output:

f1prev = -4.0935e+173
f2prev = -5.711e+160
f3prev = -8.6914e+213

Figure 4 shows the actual values of accelerometer and gyroscope with the errors. The blue color represent the output of accelerometer the green color represents gyroscope.
In figure 5 the values of the nth iteration is shown in the plot where the error is reduced to the maxim extent. Here the x axis represents time and y axis represents the performance of INS in X, Y and Z axis separately.

6. Conclusion

To design the Integration of GPS/ INS navigation system with application of Fuzzy Corrections was done and estimated the predicted value of error as shown in the Figure 4.Theoretical analysis and simulation results presented in the report showed that the kalman filter reduced the error in gyroscope and accelerometer to the maximum extent.

7. Future Scope

In future we can use Adaptive Neuro Fuzzy Inference System (ANFIS) for further error reduction in values of accelerometer and gyroscope.

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