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A Novel Data Fusion of Navigation and Surveillance Facilities using Multi Dimensional Kalman Filter Algorithm in Linux Environment for Optimal Air Space Management

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Abstract

A compact system which takes the data from Global Positioning System(GPS), Secondary Surveillance Radar(SSR) and a communication navigation and surveillance system, namely Very High Frequency Omni Range(VOR) and reduces the errors is designed developed and realized, which can give better positional accuracy for air traffic controlling officer(ATCO), as well as to the pilot. The process of obtaining the position information onboard, which is termed as navigation can be obtained by VOR and GPS, where as the process of obtaining the aircraft position on ground by the ATCO is called surveillance, which is obtained by radar. This system can be used both for navigation and surveillance as it integrates data received by GPS, Radar(SSR) and VOR. The system can be utilized to supplement both ground based data and satellite based data. The attempt in this paper is claimed as novel, as the entire list of state variables for the aircraft can not be provided by any one sensor at normally desired level of accuracy and dependability. A multi dimensional kalman filter algorithm is applied on a Broadcom BCM2836R processor in Linux environment using mathematica10 to achieve this objective.

Keywords: GPS,VOR,RADAR,SSR, Kalman Filter, Navigation, Surveillance, ATCO, Linux, Mathematica10

1. INTRODUCTION

The navigational aids are commonly known as nav-aids which are a set of ground based as well as satellite based facilities provide to a pilot of an aircraft positional guidance in the space with reference to the ground references. Navigational aids are classified into three groups, namely long range aids. short range aids and terminal aids. LORAN-C, DECCA come under the category of long range navigational aids. DECCA is a oldest electromagnetic radio position timing system. It is widely adopted in position fixing system and it takes observations from 6 transmission stations using phase differencing techniques. It is operated up to a range of 240 nautical miles (nmi) with accuracy of 50 to 100m.LORAN-C (LF version of LORAN) is medium to long-range low frequency time difference measurement system. A master and four secondary transmission stations transmit a set of radio pulses centred around 100 KHz in precise time sequences. Receiver measures the difference in time interval between these transmissions from different stations. Then it produces a hyperbolic line position based on time difference. It is operated up to a range of 1500km.

OMEGA is a very-long-range, very-low-frequency (VLF) radio navigation system operating in the internationally allocated navigation band between 10-14KHz. Omega is based on phase differencing techniques rather than time differences. A pair of transmitting stations provides the navigation with a family of hyperbolic lines of position and eight transmitting stations with 5000-6000 nautical miles (nmi) baselines will give a global coverage. Omega is used primarily because as 'Stringer' observed at a meeting of the British Institute of Navigation. 'It satisfies the three R's – Reliability, Redundancy and Range'. DECCA works through taking observations to pairs of six transmission stations using phase differencing techniques. These give rise to hyperbolic lines of position. It operates in 70-130 KHz frequency range.The short range nav-aids are called enroute-nav-aids, which define the airways and are used for locating the reporting points. Very high frequency omni range (VOR) is the work horse of enroute air navigation. It provides azimuthal guidance to the aircraft up to 200nmi and operates in the range of 108 to 118MHz.VOR is the most significant aviation inventionin the year 1950s.By using VOR pilot can accurately navigate from point A to point B.The Terminal aids are the most sensitive aids, which help the pilot in final phase of the landing. The guidance provided must be of very high integrity to ensure a very high probability of success for each landing. Primary Surveillance Radar(PSR) and Secondary Survillance Radar (SSR) come under this catogary. These facilities play a vital role when the visibility is poor and cloud ceiling is low. Instrument landing system (ILS) also comes in this category. In 1973 the US Dept. Of Defence (DOD) decided to establish, develop, test, acquire and deploy a space borne Global Positioning System (GPS). The result of this decision is the present NAVSTAR GPS (Navigation Satellite Timing and Ranging Global Positioning System). The GPS is proved to be an all-whether, space-based navigation system. The primary goal for developing the GPS was of military nature. The multi-purpose usage of

NAVSTAR GPS has developed enormously within the last two and half decades. With the elimination of SA (Selective Availability) on May 2nd , 2000, the usefulness of the system for civilian users was even more pronounced. Today a full constellation of at least 28 satellites are available.

A system which integrates the data received from GPS, Radar and other CNS equipment is developed which can give more accurate 'state vector' that fully describe the translational motion of aircraft . The process is usually called obtaining ' Navigation data ' which can be sent to other on board sub systems namely –to the flight control, flight management, engine control, communication control etc. The specialty of this integrated multi-sensor system is that it fuses the data received from various platforms namely, GPS data which is basically satellite dependent and radar (SSR) and VOR data which is ground based. When the state vector is measured and calculated on board the process is called 'Navigation'. And when the state vector is measured and calculated on ground, the process is called 'Surveillance'. The developed system can be utilized both for Navigation and Surveillance. The system is very small, light in weight and compact so that it can be accommodated as a sub-system in any environment.

Sensor description and error analysis was done in respect of three sensors, namely VOR, GPS and SSR reported in [1],[2] and [3]and the results are enumerated. It was found that the aggregate azimuth error is $\pm 5^0$ for VOR reduced to $\pm 1^0$ using scalar kalman filter. The altitude error in respect of GPS also reduced significantly using scalar kalman filter. The error in altitude in respect of SSR reduced from 25m to 5m using scalar kalman filter which is very significant improvement. In this paper vector kalman filter algorithm is used with Broadcom BCM 2836R processor in Linux environment to combine the above three sensor data using Mathematica 10.

2 MULTI DIMENSIONAL KALMAN FILTER

In case of simultaneous estimation of a number of variables the vector equations are formulated. The estimation problem for multidimensional systems is formulated in terms of vectors and matrices. Since there is equivalence between scalar and matrix operations the equations of scalar Kalman filter are extended to vector /multidimensional Kalman filter as follows:

Model : $X(k) = AX(k-1) + Bu(k) + W(k)$ (1)

$Y(k) = CX(k) + V(k)$ (2)

Predict : $\hat{x}(k) = A\hat{x}(k-1) + BU(k) + W(k)$ (3)

$P(k) = AP(k-1)A^T + Q(k)$ (4)

Update :

$\hat{x}(k) = \hat{x}(k-1) + G(k)\{Y(k) - C.\hat{x}(k-1)\}$ (5)

$G(k) = \frac{P(k-1)C^T}{C\,P(k-1)\,C^T + R}$ (6)

$P(k) = (I - G(k)C)P(k-1)$ (7)

In the above equations, X is state variable vector, U is control variable vector, Y is measurement variable vector, A is state transition matrix, B is control matrix, C is measurement matrix, W is state noise matrix, V is measurement noise matrix, R is sensor covariance matrix(measurement noise matrix),K is Kalman gain matrix, P is process covariance matrix, I is identity matrix, Q is process noise covariance matrix.
In order to achieve sensor data fusion the above equations are converted into a flow-chart.

6 DATA SIMULATION AND FUSION

The three sensor data namely VOR, SSR and GPS is simulated and used as input to the multidimensional Kalman filter written in Mathematica-10 in the following manner:

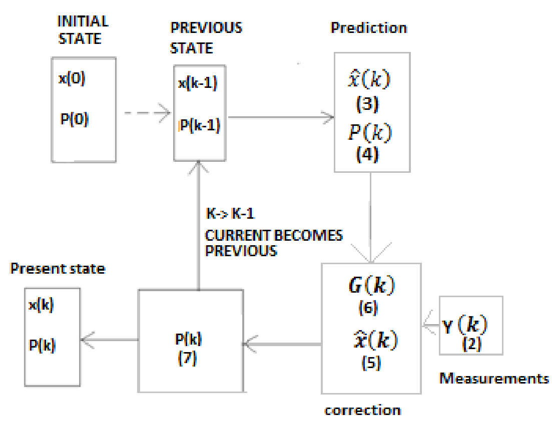

Figure : 1 Kalman Filter Multi Dimensional Model

VOR data:
Initial azimuth $X_0 = 20^0$
Error in measurement = 20^0
Initial error in measurement = 18^0

True azimuth for 10 iterations =[0, 36, 72, 108,144,180,216,252,288,324]
Measured azimuth for 10 iterations (Simulated: Error taken as $\pm 5^0$ degrees)= -8,31,82,116,141,179,221,258,278,329

SSR data:
Initial altitude $Y_0 = 100$
Error in measurement = 50
Initial error in measurement = 50
True altitude for 10 iterations = 0,200,400,600,800,1000,1200,1400,1600,1800
Measured altitude for 10 iterations (Simulated: Error taken as ± 100 units) = 3,129,370,544,780,1072,1238,1348,1617,1875

GPS data:
Initial altitude $Z_0 = 1208430$
Error in measurement = 450
Initial error in measurement = 10,000
True altitude for 10 iterations = 1208445 (Taken as constant)

Measured altitude for 10 iterations (Simulated: Error taken as ± 450units)= 1208350,1208630,1208510,1208220,1208410,1208530,1208010, 1208500,1208410,1208860

The above data from three sensors namely VOR, SSR, GPS is converted into matrix/vector form to give as input to multi dimensional Kalman filter as follows:

i) The initial state vector X(0)= $\begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \end{bmatrix} = \begin{bmatrix} 20 \\ 100 \\ 1208430 \end{bmatrix}$

Where X_0 = initial value of VOR azimuth

Table 1 : Multi dimensional kalman filter output

SNO	G(k) Kalman Gain	X(k) Expected Value	P(k) Error in X(k)
1	**{{0.473684,0.,0.}, {0.,0.5,0.}, {0.,0.,0.956938}}**	**{{6.73684}, {51.5}, {1.20835*10^6}}**	**{{9.47368,0.,0.}, {0.,25.,0.}, {0.,0.,430.622}}**
2	**{{0.321429,0.,0.}, {0.,0.333333,0.}, {0.,0.,0.488998}}**	**{{14.5357}, {77.3333}, {1.20849*10^6}}**	**{{6.42857,0.,0.}, {0.,16.6667,0.}, {0.,0.,220.049}}**
3	**{{0.243243,0.,0.}, {0.,0.25,0.}, {0.,0.,0.328407}}**	**{{30.9459}, {150.5}, {1.2085*10^6}}**	**{{4.86486,0.,0.}, {0.,12.5,0.}, {0.,0.,147.783}}**
4	**{{0.195652,0.,0.}, {0.,0.2,0.}, {0.,0.,0.247219}}**	**{{47.587}, {229.2}, {1.20843*10^6}}**	**{{3.91304,0.,0.}, {0.,10.,0.}, {0.,0.,111.248}}**
5	**{{0.163636,0.,0.}, {0.,0.166667,0.}, {0.,0.,0.198216}}**	**{{62.8727}, {321.}, {1.20842*10^6}}**	**{{3.27273,0.,0.}, {0.,8.33333,0.}, {0.,0.,89.1972}}**
6	**{{0.140625,0.,0.}, {0.,0.142857,0.}, {0.,0.,0.165426}}**	**{{79.2031}, {428.286}, {1.20844*10^6}}**	**{{2.8125,0.,0.}, {0.,7.14286,0.}, {0.,0.,74.4417}}**
7	**{{0.123288,0.,0.}, {0.,0.125,0.}, {0.,0.,0.141945}}**	**{{96.6849}, {529.5}, {1.20838*10^6}}**	**{{2.46575,0.,0.}, {0.,6.25,0.}, {0.,0.,63.8751}}**
8	**{{0.109756,0.,0.}, {0.,0.111111,0.}, {0.,0.,0.124301}}**	**{{114.39}, {620.444}, {1.2084*10^6}}**	**{{2.19512,0.,0.}, {0.,5.55556,0.}, {0.,0.,55.9354}}**
9	**{{0.0989011,0.,0.}, {0.,0.1,0.}, {0.,0.,0.110558}}**	**{{130.571}, {720.1}, {1.2084*10^6}}**	**{{1.97802,0.,0.}, {0.,5.,0.}, {0.,0.,49.7512}}**
10	**{{0.09,0.,0.}, {0.,0.0909091,0.}, {0.,0.,0.099552}}**	**{{148.43}, {825.}, {1.20836*10^6}}**	**{{1.8,0.,0.}, {0.,4.54545,0.}, {0.,0.,44.7984}}**

Y_0 = initial value of SSR altitude

Z_0 = initial value of GPS altitude

ii) The initial error co-variance matrix P(0)= $\begin{bmatrix} 18 & 0 & 0 \\ 0 & 50 & 0 \\ 0 & 0 & 10000 \end{bmatrix}$

iii) The process noise covariance matrix Q is ignored for the purpose of ease of calculation. Similarly V and W matrices are also ignored.

iv)The measurement noise co-variance matrix R =

$$\begin{bmatrix} 20 & 0 & 0 \\ 0 & 50 & 0 \\ 0 & 0 & 450 \end{bmatrix}$$

v)The connection matrices $C1,\ I1,\ H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

vi)The state transition matrix $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ as all three state variables are uncorrelated. B and U matrices are zero as there are no control variables in this case.

vii) Matrix representing actual values of VOR, SSR, GPS for 10 iterations T = {{1,{0,0,1208445}},{2,{36,200,1208445}},{3,{72,400,1208445}},{4,{108,600,1208445}},{5,{144,800,1208445}},{6,{180,1000,1208445}},{7,{216,1200,1208445}},{8,{252,1400,1208445}},{9,{288,1600,1208445}},{10,{324,1800,1208445}}}

viii) Matrix representing measured values of VOR, SSR, GPS for 10 iterations Z= {{1,{-8,3,1208350}},{2,{31,129,1208630}},{3,{82,370,1208510}},{4,{116,544,1208220}},{5,{141,780,1208410}},{6,{179,1072,1208530}},{7,{221,1238,1208010}},{8,{258,1348,1208500}},{9,{278,1617,1208410}},{10,{329,1874,1208060}}}

4. RESULTS AND DISCUSSION

The data obtained from simulation of VOR, SSR and GPS vectors /matrices is applied to a multi-dimensional Kalman Filter algorithm for which the program is written in Mathematica-10, to get kalman gain G(k),expected value X(k) and error co-variance matrix P(k) is given below, for 10 iterations in Tab. 1

Perusal of the vector kalman filter output in Tab. 1 shows that the Kalman gain is reducing gradually from first iteration to the tenth iteration. Also observation of the column for error in expected value shows that the error is reduced from 9.47 to 1.8 degrees of azimuth in case of VOR, and the error is reduced from 25 to 4.545 in altitude in case of SSR, and finally the error is reduced from 430.6 to 44.798 in altitude in case of GPS. The reduction in the error in expected value is achieved gradually from iteration 1 to iteration 10 shows that the vector/multi-dimensional kalman filter is stable and well tuned.

5. CONCLUSIONS

A system which can reduce the errors in the data from Global Positioning System(GPS), Secondary Surveillance Radar(SSR) and a communication navigation and surveillance system, namely Very High Frequency Omni Range(VOR) is realized, which can give better positional accuracy for air traffic controlling officer(ATCO), as well as to the pilot. Aircraft density is an important factor for vectoring aircraft in an international airport scenario. The ATCO depends heavily on SSR data as well as GPS data while vectoring the incoming and outgoing aircraft and if the accuracy of GPS and SSR data is increased it will be of immense help to the ATCO. Similarly increasing the VOR azimuth data accuracy is an important aspect for the pilot, while determining his position with reference to any enroute VOR or airport located VOR. Hence this system can be used both for navigation and surveillance as it integrates data received by GPS, Radar(SSR) and VOR. The system can be utilized to supplement both ground based data and satellite based data. A multi-dimensional Kalman Filter algorithm is used with Mathematica-10 in Linux environment and it is found that there is significant error reduction in all the three sensors namely VOR, SSR and GPS. The design of the system is clamed as novel, as the system is very compact, powerful and fits into any equipment with ease, and also the entire list of state variables for an aircraft cannot be provided with any one sensor at normally desired levels of accuracy and dependability. Fused data from multiple sensors is used to overcome this problem. The paper is ended with citation of the work already carried out by the author(S). However, bibliography appended the references is to improve the bore sight of this work.

Appendix-A

Glossary

A.1.VOR: Very high frequency omni-range

VOR Provides Aircraft radial with respect to a ground station. In other words, the VOR system only informs us of the aircraft location as an entity seen by a ground VOR transmitter. However, we have no knowledge whatsoever on the heading of the aircraft. The radial of the aircraft is obtained by taking the phase difference of two signals reference Phase Signal (R) & Variable Phase Signal (V) transmitted by the ground station V-Airway, track intercept, triangular position fix etc. are few of the applications of VOR.

A.1.1. Advantages

VOR is more efficient than ADF since its indicator point to the ground VOR transmit system. Whereas ADF provides a relative bearing corresponding to the offset between the aircraft longitudinal axis and the NDB, and hence does not point to the ground base beacon.

A.1.2.Disadvantages

- Error is approx. about +/- 5 ^{0} It is limited to LOS due to VHF band operation.
- VOR signals are either reflected or blocked or distorted due to buildings,Mountains,Fences, power lines etc.
- At higher altitude interference may occur between two ground stations operated at the same frequency.
- VOR does not provide the aircraft heading, it only points to the ground station.

A.2. Secondary surveillance radar (SSR)

A radar system used in air traffic control (ATC), that not only detects and measures the position of aircraft i.e. bearing, but also requests additional information from the aircraft itself such as its identity and altitude. Unlike primary radar systems that measure the bearing of targets using the detected reflections of radio signals, SSR relies on targets equipped with a radar transponder, that replies to each interrogation signal by transmitting a response containing encoded data. SSR is based on the military identification friend or foe (IFF) technology originally developed during World War II, therefore the two systems are still compatible. Monopulse secondary surveillance radar (MSSR), Mode S, TCAS and ADS-B are similar modern methods of secondary surveillance. It has short comings such as height information is limited with the problems like, co-channel interference, fruit and garble.

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