IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 8, Issue 6, June 2020

An Improved Data Fusion of VOR, SSR, GPS, DVOR and DME Facilities using Multi-Dimensional Kalman Filter for Optimal and Economic Air Traffic control

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Abstract: In this paper a system which can give better location accuracy of an aircraft for an Air Traffic Controlling Officer (ATCO) and also to the Pilot taking inputs from various navigation and surveillance facilities like Secondary Surveillance Radar (SSR), Global Positioning System (GPS), Very High Frequency Omni Range (VOR) or Doppler VOR(DVOR) and Distance Measuring Equipment (DME) is designed, developed and realized. Navigation of an aircraft is the process of obtaining position/ location information onboard which can be obtained by sensors like VOR/ DVOR, DME and GPS. Surveillance is the process of obtaining same information namely location of an aircraft by the ATCO which is obtained from Radar. The system designed can be used for both navigation and surveillance as it integrates data obtained from SSR, GPS, VOR/ DVOR and DME. The designed system is claimed as novel as it can be used to supplement ground based as well as satellite based data in addition to navigation and surveillance economically at normally designed levels of accuracy and dependability. A multidimensional Kalman filter is used on a Broadcom BCM2837R processor in Linux environment using Mathematica 11 to achieve this objective.

Keywords: SSR, VOR, DVOR, GPS, Radar, DME, Navigation, Surveillance, Multidimensional Kalman filter, Linux, ATCO, Mathematica 11

I. 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. 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 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/ DVOR is the most significant aviation inventionin the year 1950s.By using VOR/ DVOR and DME combination 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 Surveillance Radar (SSR) come under this category. 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

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 8, Issue 6, June 2020

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 2^{nd}, 2000, the usefulness of the system for civilian users was even more pronounced. Today a full constellation of at least 28 satellites are available. The Distance Measuring Equipment (DME) provides the slant range distance between the aircraft and the selected DME ground station. DME operates in L-band from 962 MHz to 1213 MHz

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/ DVOR and DME 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/ DVOR, 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 and $\pm 3^0$ in respect of DVOR, 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. These three sensor outputs are combined successfully using a vector Kalman filter and the results are reported in [4]. In this paper we have added two more sensors namely DVOR and DME with simulated data, taking the total number of sensors to five. A vector kalman filter algorithm is used with Broadcom BCM 2837R processor in Linux environment to combine the above five sensors simulated data using Mathematica 11.

II. 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 :
$$X(k) = AX(k-1) + Bu(k) + W(k) \quad (1)$$
$$Y(k) = CX(k) + V(k) \quad (2)$$

Predict :
$$\hat{x}(k) = A\hat{x}(k-1) + BU(k) + W(k) \quad (3)$$
$$P(k) = AP(k-1)A^T + Q(k) \quad (4)$$

Update :
$$\hat{x}(k) = \hat{x}(k-1) + G(k)\{Y(k) - C.\hat{x}(k-1)\} \quad (5)$$
$$G(k) = \frac{P(k-1)C^T}{C\,P(k-1)\,C^T + R} \quad (6)$$
$$P(k) = (I - G(k)C)P(k-1) \quad (7)$$

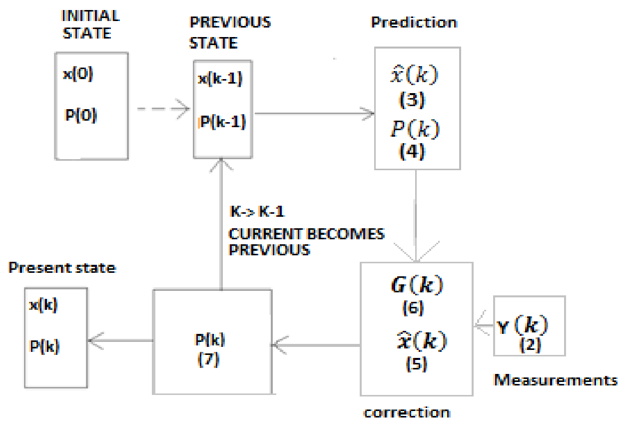

Figure : 1 Kalman Filter Multi Dimensional Model

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 8, Issue 6, June 2020

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),G 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.

III. DATA SIMULATION AND FUSION

The five sensor data namely VOR, SSR, GPS, DVOR and DME is simulated and used as input to the multidimensional Kalman filter written in Mathematica-11 in the following manner:

1. VOR data:
Initial azimuth $= 20$ deg
Error in measurement = 20 deg
Initial error = 18 deg
True azimuth for 10 iterations = (0,36,72,108,144,180,216,252,288,324) deg
Measured azimuth for 10 iterations (Simulated: Error taken as $\pm 5^0$) = (-8,31,82,116,141,179,221,258,278,329) deg

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

3. GPS data:
Initial altitude $= 1208430$m
Error in measurement = 450 m
Initial error = 10,000 m
True altitude for 10 iterations = 1208445 m (Taken as constant)
Measured altitude for 10 iterations (Simulated: Error taken as $\pm$ 450units)= (1208350,1208630,1208510,1208220,1208410,1208530,1208010,
1208500,1208410,1208860) m

4. DVOR data:
Initial azimuth 10 deg
Error in measurement = 10 deg
Initial error = 10 deg
True azimuth for 10 iterations = (0,36,72,108,144,180,216,252,288,324) deg
Measured azimuth for 10 iterations (Simulated: Error taken as $\pm 3^0$)=(-3, 40, 70, 110, 149, 175, 220, 257, 284, 326) deg

5. DME data:
Initial distance 16 NM
Error in measurement = 16 NM
Initial error = 15 NM
True distance for 10 iterations = (0, 20, 40, 60, 80, 100, 120, 140, 160, 180)NM
Measured distance for 10 iterations (Simulated: Error taken as ± 10NM)=(-4, 27, 45, 55, 75, 108, 128, 145, 168, 175) NM
The above data from five sensors namely VOR, SSR, GPS, DVOR and DME is converted into matrix/vector form to give as input to multi dimensional Kalman filter as follows:

i) The initial state vector X(0) = {{20},{100},{1208430},{10},{16}}
ii) The initial error co-variance matrix P(0)= $\{\{18, 0, 0, 0, 0\}, \{0, 50, 0, 0, 0\}, \{0, 0, 10\,000, 0, 0\}, \{0, 0, 0, 10, 0\}, \{0, 0, 0, 0, 15\}\}$
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 = $\{\{20, 0, 0, 0, 0\}, \{0, 50, 0, 0, 0\}, \{0, 0, 450, 0, 0\}, \{0, 0, 0, 10, 0\}, \{0, 0, 0, 0, 16\}\}$

IJIREEICE

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

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v) The connection matrices
H= {{1, 0, 0, 0, 0},{0, 1, 0, 0, 0},{0, 0, 1, 0, 0},{0, 0, 0, 1, 0},{0, 0, 0, 0, 1}}

I1= {{1, 0, 0, 0, 0},{0, 1, 0, 0, 0},{0, 0, 1, 0, 0},{0, 0, 0, 1, 0},{0, 0, 0, 0, 1}}
C1= {{1, 0, 0, 0, 0},{0, 1, 0, 0, 0},{0, 0, 1, 0, 0},{0, 0, 0, 1, 0},{0, 0, 0, 0, 1}}

vi) The state transition matrix A = {{1, 0, 0, 0, 0}, {0, 1, 0, 0, 0}, {0, 0, 1, 0, 0}, {0, 0, 0, 1, 0}, {0, 0, 0, 0, 1}} as all five 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, DVOR, DME for 10 iterations T =
{{0, 0, 1208 445, 0, 0},{36, 200, 1208 445, 36, 20},
{72, 400, 1208 445, 72, 40},{108, 600, 1208 445, 108, 60},
{144, 800, 1208 445, 144, 80},{180, 1000, 1208 445, 180, 100},
{216, 1200, 1208 445, 216, 120},{252, 1400, 1 208 445, 252, 140},
{288, 1600, 1208 445, 288, 160},{324, 1800, 1 208 445, 324, 180}}

viii) Matrix representing measured values of VOR, SSR, GPS, DVOR & DME for 10 iterations Z= {{-8, 3, 1 208 350,-3,-4},{31, 129, 1 208 630, 40, 27},
{82, 370, 1 208 510, 70, 45},{116, 544, 1 208 220, 110, 55},
{141, 780, 1 208 410, 149, 75},{179, 1072, 1 208 530, 175, 108},
{221, 1238, 1 208 010, 220, 128},{258, 1348, 1 208 500, 257, 145},
{278, 1617, 1 208 410, 284, 168},{329, 1874, 1 208 060, 326, 175}}

IV. RESULTS AND DISCUSSION

The data obtained above from simulation of VOR, SSR, GPS, DVOR and DME vectors /matrices is applied to a multi-dimensional Kalman Filter algorithm for which the program is written in Mathematica-11, to get kalman gain G(k),expected value X(k) and error co-variance matrix P(k) is given below, for 10 iterations.

Multi dimensional kalman filter output:

1) **Expected value X(k):**

{ 1. {{6.74}, {51.50}, {1208350}, {3.50}, {6.32}}},
2. {{14.53}, {77.33}, {1208490}, {15.67}, {13.06}}},
3. {{30.95}, {150.50}, {1208500}, {29.25}, {20.92}}},
4. {{47.59}, {229.2}, {1208430}, {45.4}, {27.64}}}
5. {{62.87}, {321.0}, {1208420}, {62.67}, {35.45}}},
6. {{79.20}, {428.29}, {1208440}, {78.71}, {45.72}}},
7. {{96.68}, {529.5}, {1208380}, {96.38}, {55.92}}},
8. {{114.4}, {620.4}, {1208400}, {114.2}, {65.74}}},
9. {{130.57}, {720.1}, {1208400}, {131.2}, {75.9}}},
10. {{148.2}, {825.0}, {1208360}, {148.9}, {84.86}}}}

2) **Error in Expected value P(k):**

{ {1. {{9.47, 0, 0, 0, 0}, {0, 25.0, 0, 0, 0}, {0, 0, 430.6, 0, 0}, {0, 0, 0, 5, 0},{0, 0, 0, 0, 7.74}}},
{2. {{6.43, 0, 0, 0, 0}, {0, 16.67, 0, 0, 0}, {0, 0, 220.0, 0, 0}, {0, 0, 0, 3.33, 0},{0, 0, 0, 0, 5.21}}},
{3. {{4.86, 0, 0, 0, 0}, {0, 12.5, 0, 0, 0}, {0, 0, 147.78, 0, 0}, {0, 0, 0, 2.5, 0},{0, 0, 0, 0, 3.93}}},
{4. {{3.91, 0, 0, 0, 0}, {0, 10.0, 0, 0, 0}, {0, 0, 111.25, 0, 0}, {0, 0, 0, 2, 0},{0, 0, 0, 0, 3.15}}},
{5. {{3.27, 0, 0, 0, 0}, {0, 8.33, 0, 0, 0}, {0, 0, 89.2, 0, 0}, {0, 0, 0, 1.67, 0},{0, 0, 0, 0, 2.64}}},
{6. {{2.81, 0, 0, 0, 0}, {0, 7.14, 0, 0, 0}, {0, 0, 74.44, 0, 0}, {0, 0, 0, 1.43, 0},{0, 0, 0, 0, 2.26}}},
{7. {{2.47, 0, 0, 0, 0}, {0, 6.25, 0, 0, 0}, {0, 0, 63.88, 0, 0}, {0, 0, 0, 1.25, 0},{0, 0, 0, 0, 1.98}}},
{8. {{2.2, 0, 0, 0, 0}, {0, 5.56, 0, 0, 0}, {0, 0, 55.9, 0, 0}, {0, 0, 0, 1.11, 0},{0, 0, 0, 0, 1.76}}},
{9. {{1.98, 0, 0, 0, 0}, {0, 5.0, 0, 0, 0}, {0, 0, 49.76, 0, 0}, {0, 0, 0, 1, 0},{0, 0, 0, 0, 1.59}}},
{10. {{1.8, 0, 0, 0, 0}, {0, 4.55, 0, 0, 0}, {0, 0, 44.8, 0, 0}, {0, 0, 0, 0.91, 0},{0, 0, 0, 0, 1.45}}}}

3) **Kalman Gain G(k):**

{ {1. {{0.474, 0, 0, 0, 0}, {0, 0.5, 0, 0, 0}, {0, 0, 0.957, 0, 0}, {0, 0, 0, 0.5, 0},{0, 0, 0, 0, 0.484}}},
{2. {{0.321, 0, 0, 0, 0}, {0, 0.333, 0, 0, 0}, {0, 0, 0.489, 0, 0}, {0, 0, 0, 0.333, 0},{0, 0, 0, 0, 0.326}}},
{3. {{0.243, 0, 0, 0, 0}, {0, 0.25, 0, 0, 0}, {0, 0, 0.328, 0, 0}, {0, 0, 0, 0.25, 0},{0, 0, 0, 0, 0.246}}},
{4. {{0.196, 0, 0, 0, 0}, {0, 0.2, 0, 0, 0}, {0, 0, 0.247, 0, 0}, {0, 0, 0, 0.2, 0},{0, 0, 0, 0, 0.197}}},

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{5. {{0.164, 0, 0, 0, 0}, {0, 0.167, 0, 0, 0}, {0, 0, 0.198, 0, 0}, {0, 0, 0, 0.167, 0},{0, 0, 0, 0, 0.165}}},
{6. {{0.141, 0, 0, 0, 0}, {0, 0.143, 0, 0, 0}, {0, 0, 0.165, 0, 0}, {0, 0, 0, 0.143, 0},{0, 0, 0, 0, 0.142}}},
{7. {{0.123, 0, 0, 0, 0}, {0, 0.125, 0, 0, 0}, {0, 0, 0.142, 0, 0}, {0, 0, 0, 0.125, 0},{0, 0, 0, 0, 0.124}}},
{8. {{0.110, 0, 0, 0, 0}, {0, 0.111, 0, 0, 0}, {0, 0, 0.124, 0, 0}, {0, 0, 0, 0.111, 0},{0, 0, 0, 0, 0.110}}},
{9. {{0.099, 0, 0, 0, 0}, {0, 0.1, 0, 0, 0}, {0, 0, 0.111, 0, 0}, {0, 0, 0, 0.1, 0},{0, 0, 0, 0, 0.099}}},
{10. {{0.09, 0, 0, 0, 0}, {0, 0.091, 0, 0, 0}, {0, 0, 0.099, 0, 0}, {0, 0, 0, 0.091, 0},{0, 0, 0, 0, 0.09}}}}

Perusal of the vector kalman filter output shows that the Kalman gain is reducing gradually from first iteration to the tenth iteration. Also observation of the 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 4.55 in altitude in case of SSR, the error is reduced from 430.6 to 44.8 in altitude in case of GPS, the error in azimuth from 5 to 0.91 degrees in case of DVOR and from 7.74 NM to 1.45 NM in case of DME. 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.

V. CONCLUSION

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/ DVOR) and Distance Measuring Equipment (DME) 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/ DVOR azimuth data accuracy is an important aspect for the pilot, while determining his position with reference to any en-route VOR/ DVOR or airport located VOR/ DVOR. Hence this system can be used both for navigation and surveillance as it integrates data received by GPS, Radar (SSR) and VOR/ DVOR. 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-11 in Linux environment and it is found that there is significant error reduction in all the five sensors namely VOR, DVOR, SSR, GPS and DME. The design of the system is claimed 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 to improve the bore site of the work.

APPENDIX – A

In the earlier works carried out [4] VOR and SSR were discussed in the appendix. In this appendix remaining equipment namely DVOR and DME basic principles are presented.

A. 1. DVOR: Doppler Very High frequency Omni Range

In the DVOR system, the carrier is amplitude modulated with 30 Hz signal and is radiated from an omni directional Antenna. This provides the reference signal in the system. The direction dependent signal is generated in space by switching the upper and lower side bands of carrier amplitude modulated by 9960 Hz between 48 antennas mounted in a circle at a rate of 30Hz. As the frequency deviation of the FM signal specified for VOR is +/_ 480 Hz and the time period for one rotation is 1/30 of a second. The resulting diameter of the circle is 13.5 m at 115 MHz. the aircraft receiver therefore sees a Doppler shift of the side band frequencies deviating at +/_ 480 Hz 30 times in a second. The signal is radiated anti-clockwise since the FM and AM signals have changed wrt the conventional VOR. The system provides 160 discreet operating channels within a frequency range of 108 – 117.95 MHz. The beacon output is normally 50W which provides a nominal operating range of 150 NM with best bearing accuracy. An optional variant provides a additional 50W power amplifier and combiner unit to raise the total transmitting power to 100W.

A.2. DME: Distance Measuring Equipment

The DME is a navigational system which provides slant – range distance information between the aircraft and a ground station. The frequency of interrogator is 1118MHz and that of transponder is 1181 MHz. the system consists of a transmitter-receiver (Interrogator) in the aircraft and a receiver / transmitter (transponder) at the ground station. The interrogator transmits interrogation pulses to the transponder which is triggered to transmit a sequence of reply pulses which have a predetermined time delay. The time difference between the interrogation and the reply is measured in the interrogator and translated into a distance measurement which is presented on a digital display in the aircraft cockpit and this display is continuously updated. The system provides for 252 discrete operating channels within a frequency range of 962 to 1213 MHz. the transponder output is normally 1KW peak which provides an operating range of 200NM with an accuracy of +/_ 1NM.

REFERENCES

[1] K.Rama Krishna, M.R.K.Murthy and N.S.Murtisarma, " A Novel Method for Very-high Frequency Omni Range (VOR) Azimuth Error Correction using Kalman Filter for the Improvement of Aircraft Density", IJIREEICE., Vol.5 ,issue6, June2017.
[2] K.Rama Krishna, M.R.K.Murthy and N.S.Murtisarma, " A Novel Investigation on the Analysis and Minimisation of Errors in Global Positioning System (GPS) Receiver co-ordinates using Kalman filter Algorithm for Optimal Air-space anagement,"IJTRD,Vol.4,Issue4,July,Aug,2017.
[3] K.Rama Krishna, M.R.K.Murthy, N.S.Murti sarma & P.Chadra sekhar, "Analytical study of SSR, MSSR & MODE-S parameters & investigation & improvement of altitutde accuracy of SSR using Kalaman filter algorithm for optimal air traffic control," IJATE, Vol7, No11, 2017.
[4] K.Rama Krishna, M.R.K.Murthy and N.S.Murti sarma, "A Novel Data Fusion of Navigation and Survellience Facolities using Multi Dimensional Kalman Filter Algorithm in Linux Environment for Optimal Air space Management," IJETTCS, Vol.6, Issue 6, Nov-Dec2017.

BIBLOGRAPHY

[1] Avallone,A, P.Briole, A.M.M.Balodimou, H.Billiris, O.Charade, C.Mitsakaki and Alexandre."Analysis of eleven years of deformation measured by GPS in the Corinth Rift Laboratory area," Comptes Rendus Geoscience, 336 ,(4-5): 301-311, MAR 2004.
[2] Hollenstein, C; Kahle, HG; Geiger, A; S,Jenny, S.Goes and D.Giardini, "New GPS constraints on the Africa-Eurasia plate boundary zone in southern Italy"Geophysical Research Letters, 30 (18): Art. No. 1935 SEP 20 2003.
[3] Cocard, M; Geiger, A; Kahle, HG; et al. "Airborne laser altimetry in Ionian Sea", Greece, Global & Planetary Change, 34(1-2): 87-96 Sep 2002
[4] Ganas, A; Lagios, E; Tzannetos, N "An investigation into the spatial accuracy of the IKONOS 2 orthoimagery within an urban environment" International Journal Of Remote Sensing, 23 (17): 3513-3519 SEP 2002.
[5] Luo, Y., Zhu, Y., Luo, D., Zhou, J., Song, E., Wang, D.: "Globally optimal multi-sensor distributed random parameter matrices Kalman filtering fusion with applications," Sensors, 8, pp. 8086–8103 ,2008.
[6] Carli, R., Chiuso, A., Schenato, L., Zampieri, S.: "Distributed Kalman filtering based on consensus strategies,". Technical Report, Information Engineering Department, University of Padova, Padova, Italy, 2007.
[7] Luo, D.D., Zhu, Y.M., "Applications of random parameter matrices Kalman filtering in Uncertain observation and multi-model systems,". Proc. Int. Federation of the Automatic Control, Seoul, Korea, 6–11, July, 2008
[8] Zhu, Y.M., You, Z.S., Zhao, J., Zhang, K.-S., Rong Li, X.: "The optimality for the distributed Kalman filtering fusion with feedback," Automatica, 37, pp. 1489–1493. 2001.
[9] Jiang, T., Matei, I., Baras, J.S.: "A trust-based distributed Kalman filtering approach for mode estimation in power systems". Proc. First Workshop on Secure Control Systems (SCS), Stockholm, Sweden, 12 pp. 1–6, April, 2010.
[10] Olfati-Saber, R.:, "Distributed Kalman filtering for sensor networks,".Proc. 46th IEEE Conf. on Decision and Control, ,pp. 5492–5498,2007
[11] Spanos, D.P., Olfati-Saber, R., Murray, R.M.: "Approximate distributed Kalman filtering in sensor networks with quantifiable performance,". Fourth Int. Symp. on Information Processing in Sensor Networks (IPSN-05), pp. 133–139. April 2005.
[12] Jiang, P., Zhou, J., Zhu, Y.: , "Globally optimal Kalman filtering with finite-time correlated noises," 49th IEEE Conf. on Decision and Control, 15–17 December, 2010, Hilton Atlanta Hotel, Atlanta, GA, USA, pp. 5007–5012 .
[13] Govaers, F., Koch, W.: , "Distributed Kalman filter fusion at arbitrary instants of time," 13th Conf. on Information Fusion (FUSION),26–29, Sensor Data and Inf. Fusion, University of Bonn, Bonn, Germany, pp. 1–8, July 2010.
[14] Deng, Z.L., Gao, Y., Mao, L., Li, Y., Hao, G.: "New approach toinformation fusion steady-state Kalman filtering,"Automatica, 41, (10), pp. 1695–1707,2005.
[15] Yingting, L., Yunmin, Z.:„Yingting, L., Yunmin, Z.: "Distributed Kalman filtering fusion with packet loss or intermittent communications from local estimators to fusion center,". Proc. 29th Chinese Control Conf.Beijing, China, pp. 4768–477529–31 July, 2010.
[16] Olfati-Saber, R.: , "Distributed Kalman filter with consensus filters,".Proc. 44th Em-bedded IEEE Conf. Decision and Control, Seville, Spain, , pp. 8179–8184, December 2005.
[17] Kirti, S., Scaglione, A.,"Scalable distributed Kalman filtering through consensus". Proc. IEEE Int. Conf. on Acoustics, Speech and Signal Processing, ICASSP, April 2008.
[18] Saber, O.R.: "Distributed Kalman filter for sensor", Proc.46th IEEE Conf. on Decision & Control, New Orleans, pp.5492–5498 Dec 2007.
[19] Alriksson, P., Rantzer, A.: "Experimental evaluation of a distributed Kalman filter algo,". Proc. 46th IEEE Conf. on Decision & Control, 2007
[20] Schenato, L., Carli, R., Chiuso, A., Zampieri, S.: "Distributed Kalman filtering based on consensus strategies," IEEE J. Sel. Areas Commun., , 26, (4), pp. 622–633,2008
[21] XiaoJing, S., YingTing, L., YunMin, Z., EnBin, S.: "Globally optimal distributed Kalman filtering fusion", Sci. China Inf. Sci., ", 55, (3), pp. 512–529; DOI: 10.1007/s11432-011–4538-7,2012
[22] Quirino, R.B., Bottura, C.P.: "An approach for distributed Kalman filtering", SBA Control Autom., , 12, (1), pp. 19–28, 2001
[23] Quirino, R.B., Bottura, C.P., Costa, F.J.T.: "A computational structurefor parallel and distributed Kalman filtering,". Proc. 12th Brazilian Automatic Control Conf., Uberlandia-MG, Brazil, 14–18 September, 1998
[24] Xu,J, E.Song, Y.Luo, Y.Zhu, " Optimal distributed kalaman filtering fusion algorithm without invertibility of estimation error and sensor noise Covariance,"IEEE Signal processing Ltrs, Vol.19,Issue1, P.55-58, Jan2012.
[25] Y. M. Zhu and X. R. Li, "Best linear unbiased estimation fusion,", Int. Conf. Information Fusion, Sunnyvale, CA, Jul. 1999.
[26] X. R. Li,Y.M.Zhu, J.Wang, and C. Z. Han, "Optimal linear estimation fusion: I. unified fusion rules," IEEE Trans. Inf. Theory., vol. 49, pp. 2192–2208, 2003.
[27] C. Y. Chong, S. Mori, and K. C. Chang, "Distributed multiyarget multisensory tracking," Multitarget-Multisensor Tracking: Advanced Applications, Y. Bar-Shalom, Ed. Norwood, MA: Artech House, 1990, vol. 1, pp. 247–295.
[28] H. R. Hashmipour, S. Roy, and A. J. Laub, "Decentralized structures for parpallel Kalman filtering," IEEE Trans. Automat. Contr., vol. 33, no. 1, pp. 88–93, 1988.
[29] Y. Bar-Shalom, "On the track-to-track correlation problem," IEEE Trans. Automat. Contr., vol. 26, pp. 571–572, Apr. 1981.
[30] D. Simon & T. L.Chia, "Kalman filtering with state equality constraints," IEEE Trans. Aerosp. Electron. Syst., vol. 38, pp. 126–1136 ,Jan. 2002.
[31] S. Ko and R. R. Bitmead, "State estimation for linear systems with state equality constraints," Automatica., vol. 43, no. 8, pp. 1363–1368, 2007.
[32] Z. S. Duan andX. R. Li, "Lossless linear transformation of sensor data for distributed estimation fusion," IEEE Trans. Signal Process., vol.59, no. 1, pp. 362–372, Jan. 2011.

ISSN (Online) 2321-2004
ISSN (Print) 2321-5526

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International Journal of Innovative Research in
Electrical, Electronics, Instrumentation and Control Engineering

Vol. 8, Issue 6, June 2020

[33] S. Haykin, Adaptive Filter Theory. Englewood Cliffs, NJ: Prentice-Hall, 1996.
[34] E. B. Song, Y. M. Zhu, J. Zhou, and Z. S. You, “Optimal Kalman filtering fusion with cross-correlated sensor noises,” Automatica, vol. 43, pp. 1450–1456, 2007.
[35] A. T. Alouani and J. D. Birdwell, “Distributed estimation: Constraints on the choice of the local models,” IEEE Trans. Automat. Contr., vol.33, pp. 503–506, May 1988.
[36] Y. Bar-Shalom, “On the track-to-track corre-lation problem,” IEEE Trans. Automat. Contr., vol. AC-26, pp. 571–572, Apr. 1981.
[37] Y. Bar-Shalom and L. Campo, “The effect of the common process noise on the two-sensor fused-track covariance,” IEEE Trans. Aerosp. Electron. Syst., vol. AES-22, pp. 803–805, Nov. 1986.
[38] Y. Bar-Shalom and X. R. Li, “ Multitarget-Multisensor Tracking: Principles and Techniques. “Storrs, CT: YBS Publ., 1995.
[39] A. Ben-Israel and T. N. E. Greville, Generalized Inverses: Theory and Applications,Springer, 2nd ed., 2002.
[40] S. S. Blackman and R. F. Popoli, Design and Analysis of ModernTracking Systems. Norwood, MA: Artech House, 1999.
[41] K.C.Chang, R.K.Saha,&Y.Bar-Shalom, “on optimal track-to-track fusion,” IEEE Trans. Aerosp. Electron. Syst, vol.33, pp.1271–1276, Oct.1997
[42] C. Y. Chong, “Hierarchical estimation,” Proc. 2nd MIT/ONR Workshop on C3, Monterey, CA, July 1979.
[43] C.Y. Chong, S. Mori,W. H. Barker, and K. C. Chang, “Architectures and algorithms for track association and fusion,” IEEE AES Syst. Mag., pp. 5–13, Jan. 2000. Also in Proc. 1999 Int. Conf. on Information Fusion, Sunnyvale, CA, July, 1999.
[44] C. Y. Chong, S. Mori, and K. C. Chang, “Distributed multitarget multisensory tracking,” in Multitarget-Multisensor Tracking: Advanced Applications, Y. Bar-Shalom, Ed. Norwood, MA: Artech House, 1990.
[45] O.E.Drummond, “Track fusion with feedback,” Proc. 1996 SPIE Conf. Signal & Data Processing of Small Targets, vol.2759, pp.342–360. 1996.
[46] “A hybrid sensor fusion algorithm architecture and tracklets,”Proc. 1997 SPIE Conf. Signal and Data Processing of Small Targets, vol. 3163, , pp. 512–524, 1997
[47] “Tracklets & a hybrid fusion with process noise,” Proc. 1997SPIE Conf. Signal & Data Processing of Small Target, vol.3163, pp.512–524, 1997
[48] R. J. Fitzgerald, “Analytic track solutions with range-dependent errors,” IEEE Trans. Aerosp. Electron. Syst., vol. 36, pp. 343–348, Jan. 2000.
[49] S Grime and H. F. Durrant-Whyte, “Data fusion in decentralized sensor networks,” Contr. Eng. Practice, vol. 2, no. 5, pp. 849–863, 1994.
[49] X. R. Li, “Optimal linear estimation function for multisensor dynamic systems,” in Proc.Workshop on Multiple Hypothesis Tracking,San Diego, CA, May 2003.
[50] R. A. Horn and C. Johnson, Matrix Analysis. Cambridge, U.K.: Cambridge Univ. Press, 1985.
[51] C. L. Lawson and R. J. Hanson, Solving Least Squares Problems. Philadelphia, PA: SIAM, 1995.
[52] X. R. Li and J.Wang, “Unified optimal linear estimation fusion—Part II: Discussions and examples,” in Proc. 2000 Int. Conf. Information Fusion, Paris, France, pp. MoC2.18–MoC2.25. , July 2000
[53] X. R. Li and K. S. Zhang, “Optimal linear estimation fusion—Part IV: Optimality and efficiency of distributed