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AN ADAPTIVE ALGORITHM FOR ESTIMATION OF A STATE VECTOR IN THE SYSTEM OF REMOTELY-PILOTED AIRCRAFT CONTROL USING KALMAN FILTER

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Abstract

This paper describe the use of Kalman filter in the system of remotely-piloted vehicle control to provide a simultaneous flight of several vehicles using one ground remote control center. The filter uses the kinematic equations of motion of a point mass moving in two-dimensioned surface and the wind model load as a main disturbing factor. Measurements are made in polar coordinates, while target dynamics are estimated in rectangular coordinates, resulting in coupled linear filter equations. An adaptive procedure is used to provide the convergence properties of the algorithm. A computer simulation example, implementing the tracking algorithm, is presented as well. It is concluded that using of the developed algorithm could increase time interval between corrections of motion for a separate vehicle and increase the number of controlled vehicles to operate with one ground center.

I. Introduction

Control and monitoring systems of the remotely-piloted vehicles have received considerable attention in recent years as a possible solution to the problem of minimizing the payment for objective operations without any lost of efficiency. The costprice of remotely-piloted vehicle control system production could be reduced using modern technologies and new composite construction materials. The other way is to improve tracking and control algorithms so as to process the maximum volume of useful information received from on-board and ground measuring sensors the number of which is kept to minimum. Much efforts has been put into improving tracking algorithms(1,2) and several approaches have been proposed for the problem of maneuvering targets.(3,4) Some alternative approaches to the one described here use adaptive filters(5) and aircraft-derived data-assisted trackers.(6) Effort has also been put into developing 3-D filters and algorithms assisted by optical sensors, sensing Euler angles (7) and more recently, into analyzing the performance limitations of imaging systems used for tracking.(8)

To provide a simultaneous flight of several remotely-piloted vehicles we can operate one, common for all, ground remote control center, which could measure the range and azimuth angle of the controlled system, in the polar coordinate system with the origin fixed at the point of the ground remote control center, and transmit the control instruction, such as a required heading angle, for example, to the on-board system. In this complex, several parameters measured on-board, such as barometric altitude and heading angle, can be transmitted to the ground to assist the tracking algorithm. Some data processing may take place on-board. In this case we face a problem of how to distribute the time of ground center operation to service each of the controlled systems under which circumstance a separate vehicle can process a limited volume of information. The situation can be aggravated by the noise when measuring trajectory parameters, by the apriori uncertainty of the vehicle dynamic characteristics as well as by the factors disturbing the motion process.

The problem of getting trustworthy estimates for motion parameters of remotely-piloted vehicle, proceeding from which a control instruction is formed, with greater accuracy can be solved using a body of mathematics of Kalman discrete filters.(9) Separation of procedures of extrapolation and correction is characteristic of the filtration algorithm, this giving tactical flexibility in solving a control problem, since the rate of control and the rate of obtaining measuring information may differ greatly while servicing several vehicles simultaneously from one ground control center. An apriori uncertainty of the controlled system dynamic characteristics, which is inherent to a class of flight vehicles under consideration, requires their estimation directly in the process of operation. This problem is solved through inclusion of unknown parameters in the estimated vector. Similarly we determine parameters of the disturbing influence. But in order to reduce the volume of computational expenses and the dimensions of the problem in obtaining the estimates of these parameters we should apply an adaptive procedure.(10)

As the tracking and control algorithms are similar for each separate vehicle in the described system, only the algorithms for one controlled remotely-piloted vehicle is considered here.

A system model based on aircraft dynamics and a model of disturbing factors with unknown wind load as a main factor is first derived to provide control over a vehicle in the period between contacts based on information about changing trajectory parameters entering only from the extrapolator. Next, a full tracking algorithm is developed, which can be split, with a part operating on-board and a part operating on the ground. The tracker performance is evaluated using real data.

II. Motion models

Aircraft dynamics

The equations of kinematic motion for a point mass moving in horizontal plane are given as follows:

$$dX/dt = V\cos(Fi) + V_x \tag{1}$$

$$dX/dt = V\sin(Fi) + V_y \tag{2}$$

where X and Y are the positions of the center of mass of the vehicle in the rectangular coordinate system with the origin fixed at the point of the ground remote control center, Fi is the heading angle of the vehicle, V is the velocity of the vehicle relative to the air, which is assumed to be constant during the whole flight of the vehicle, V_x and V_y are x-body and y-body components of the wind velocity respectively.

The dynamic characteristics of the class of flight vehicles under consideration is usually described in rather simple form with a table or a curve (see Fig. 1). The dFi_b is a required angle of the turn corresponding to the maximum heading angular velocity. If $| dFi | < dFi_b$ the dynamics of the vehicle is characterized by so-called turn coefficients for the right and left turns respectively:

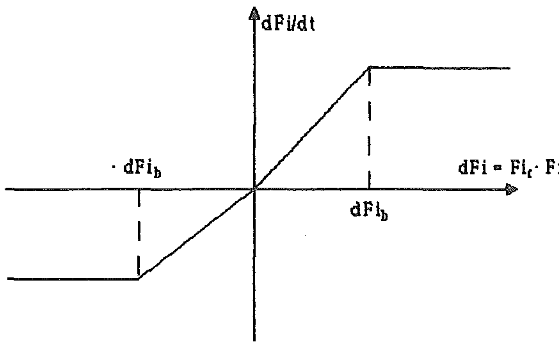

Figure 1 - Flight dynamics.

$$C_r = (dFi/dt)_{max} / dFi_b \qquad (3)$$

$$C_l = (dFi/dt)_{min} / dFi_b \qquad (4)$$

The turn coefficients are assumed to be constant during the whole flight of the vehicle and could be different for the right and left turns.

If the required heading angle is used as a control instruction, the differential equation for the heading angle is:

$$dFi/dt = f[C(Fi_r - Fi)] \qquad (5)$$

where f is a function which restrict the heading angular velocity not to be more than maximum, Fi_r is the required heading angle (the control instruction), C is a turn coefficient (right or left according to the situation).

Disturbing factors

The offered model of motion is completed by the equations describing the wind as a main disturbing factor, the parameters of which are generally unknown.

The components of the wind velocity are variable along the trajectory of the vehicle and could be modeled as a correlated random processes of position and altitude variations.[11] The wind components are assumed to be constant in a fixed point of space during the whole flight of the vehicle according to the Taylor hypothesis.[12] As the random process of wind component variations is a relatively slow one only its first derivatives with respect to the position and altitude could be taken into account.

As a consequence the differential equations for the wind velocity components are given as follows:

$$dV_x/dt = K_{Dx}\, dD/dt + K_{Hx}\, dH/dt \qquad (6)$$

$$dV_y/dt = K_{Dx}\, dD/dt + K_{Hy}\, dH/dt \qquad (7)$$

where $K_{Dx,Dy}$ is a coefficient, which connects the position variation with the x-blody and y-body wind component variations respectively, $K_{Hx,Hy}$ is a coefficient, which connects the altitude variation with the x-body and y-body wind component variations respectively, D is a distance between two points of space in horizontal plane, H is an altitude of the vehicle.

The simplified differential equation for the altitude is:

$$dH/dt = g[(dH/dt)_{max} (H_r - H)/H_D] \qquad (8)$$

where g is a function which restrict the vertical velocity of the vehicle not to be more than maximum, H_r is a required altitude of the vehicle (it is assumed to be constant), $(dH/dt)_{max}$ is a maximum vertical velocity of the vehicle corresponding to the altitude, H_D is a constant which is characteristic for the dynamics of the vehicle.

Measurement model

The measurement model consists of the available on-board measurements of the vehicle heading angle Fi_m and barometric altitude H_m, transmitted to the ground center, and of the measurements of azimuth A_m and range of the vehicle R_m.

The set of the measurement model is given in Table I.

Table I.

$Fi_m = Fi + noise$
$H_m = h + noise$
$A_m = A + noise$
$R_m = R + noise$

III. Filter algorithm

While servicing several remotely-piloted vehicles simultaneously from one ground control center the period of correction procedure for a separate vehicle may be rather greater than the period of extrapolation procedure which is chosen according to the dynamics of the vehicle so as to provide a required rate of control.

The developed model of motion allows to form a control instruction for a vehicle between contacts based on information about changing trajectory parameters entering only from the extrapolator.

For any given values for the measured parameters we can estimate states using discrete version of Kalman filter.

The state vector of the system is:

$$X = [X, Y, V, V_x, V_y, Fi, C_r, C_l, K_{Dx}, K_{Dy}, K_{Hx}, K_{Hy}]^T$$

$$
\mathbf{f}(\mathbf{X}) = d\mathbf{X}/dt = \begin{bmatrix} V\cos(Fi) + V_X \\ V\sin(Fi) + V_Y \\ 0 \\ K_{Dx}\, dD/dt + K_{Hx}\, dH/dt \\ K_{Dy}\, dD/dt + K_{Hy}\, dH/dt \\ dFi\, C_{r,l} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}
$$

The altitude of the vehicle is not included into the state vector of the system and is not being estimated as it is used only in the equation for the wind components which are rather approximate and could use directly measured value of the altitude.

The state dynamics matrix is:

$$
\mathbf{A} = d\mathbf{f}(\mathbf{X})/d\mathbf{X} = \begin{bmatrix}
0 & 0 & \cos(Fi) & 1 & 0 & -V\sin(Fi) & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \sin(Fi) & 0 & 1 & V\cos(Fi) & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & K_{Dx} & 0 & K_{Hx} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & K_{Dy} & 0 & K_{Hy} \\
0 & 0 & 0 & 0 & 0 & 0 & dFi_r & dFi_l & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

where for the right turn $dFi_l = 0$, and for the left turn $dFi_r = 0$.

The discrete dynamics matrix needed for the covariance propagation is calculated as:

$$\mathbb{A} = \mathbb{I} + dT\, \mathbf{A} \tag{9}$$

where dT is a descrete time interval.

The measurement vector is:

$$\mathbf{Z} = [R_m, A_m, Fi_m]^T$$

The measurement function vector:

$$
\mathbf{h} = \begin{bmatrix} \sqrt{X^2 + Y^2} \\ \mathrm{arctg}(Y/X) \\ Fi \end{bmatrix}
$$

and the measurement distribution matrix is:

$$
\mathbf{H} = d\mathbf{h}/d\mathbf{X} = \begin{bmatrix} X/R & Y/R & 0\,0\,0\,0\,0\,0\,0\,0\,0\,0 \\ -G/(X(G^2+1)) & 1/(X(G^2+1)) & 0\,0\,0\,0\,0\,0\,0\,0\,0\,0 \\ 0 & 0 & 0\,0\,0\,1\,0\,0\,0\,0\,0\,0 \end{bmatrix}
$$

where $G = tg(A) = Y/X$.

The measurement noise matrix:

$$
\mathbf{N} = \begin{bmatrix} S_R^2 & 0 & 0 \\ 0 & S_A^2 & 0 \\ 0 & 0 & S_{Fi}^2 \end{bmatrix}
$$

The extrapolation procedure is given by:

$$\mathbf{X}^-_{k+1} = \mathbf{X}_k + \mathbf{f}(\mathbf{X}_k)\, dT + \mathbb{A}(\mathbf{X}_k)\, dT^2/2 \tag{10}$$

$$\mathbb{P}^-_{k+1} = \mathbb{A}_k \mathbb{P}_k \mathbb{A}_k + \mathbb{Q}_k \tag{11}$$

where $\mathbb{P}$ is state-estimate error-covariance matrix, $\mathbb{Q}$ is process noise covariance matrix, the superscript minus signs on $\mathbf{X}$ and $\mathbb{P}$ represents the values of $\mathbf{X}$ and $\mathbb{P}$ before the measurement update.

The correction procedure is given by:

$$\mathbf{X}_{k+1} = \mathbf{X}^-_{k+1} + \mathbb{K}_{k+1}\, [\, \mathbf{Z}_{k+1} - \mathbf{h}(\mathbf{X}^-_{k+1})\,] \tag{12}$$

$$\mathbb{K}_{k+1} = \mathbb{P}^-_{k+1} \mathbf{H}^T_{k+1}\, [\, \mathbf{H}_{k+1} \mathbb{P}^-_{k+1} \mathbf{H}^T_{k+1} + \mathbf{N}_{k+1}\,]^{-1} \tag{13}$$

$$\mathbb{P}_{k+1} = \mathbb{P}^-_{k+1} - \mathbb{K}_{k+1} \mathbf{H}_{k+1} \mathbb{P}^-_{k+1} \tag{14}$$

where $\mathbb{K}$ is Kalman gain matrix.

As it is impossible to take into account all the disturbing factors during the flight of the vehicle and so as to improve convergence properties of the algorithm an adaptive procedure of choosing the values of the process noise covariance matrix is used [10]:

$$\mathbb{Q}_{k+1} = K_1\, \mathbb{B}_{k+1} \mathbb{B}^T_{k+1} + K_2\, \mathbb{Q}_k \tag{15}$$

where $\mathbb{B}_{k+1} = \mathbb{K}_{k+1}[\, \mathbf{Z}_{k+1} - \mathbf{h}(\mathbf{X}_{k+1})\,]$ and nondiagonal components of the process noise covariance matrix are always zeros. K_1 and K_2 are the coefficients.

The algorithm is initialized by setting the state estimate $\mathbf{X} = \mathbf{X}_0$ and the estimation error-covariance matrix $\mathbb{P} = \mathbb{P}_0$. The time update for the estimate and error covariance is performed by computing of (10) and (11) equations. The measurement update is performed by computing of the Kalman gain (12-14). The resulting $\mathbf{X}$ is the estimate of the state vector which, along with the updated error covariance matrix $\mathbb{P}$, is used as the initial condition for the next pass through the algorithm. This set of operations is correct only for the steps where the measurements are presented, but during the interval between contacts only the time update for estimate and error covariance is performed and the resulting $\mathbf{X}$ is used as the initial condition for the next pass.

IV. Simulation results.

The simulation has been employed to demonstrate the ability to control the vehicle using estimates provided by the developed tracking algorithm in spite of lack of information, as the longer the period of correction the more vehicles could be controlled with one ground remote control center.

The simulation represents the fully vehicle kinematics and dynamics. The measurements were generated from the truth model state vector and were corrupted by Gaussian white noise.

The measurement noise variances are shown in Table II and were obtained from the accuracy specifications of the proposed instruments.

Table II

Measurement	Variance (S^2)	Units	S	Units
Range (R_m)	1600	meters^2	40	m
Azimuth (A_m)	0.0003	radians^2	0.0173	radian
Heading angle (Fi_m)	0.0027	radians^2	0.0522	radian

The follows components of the state vector could be initialized using the first measurement information:

$$Xo = Ro_m \cos(Ao_m)$$

$$Yo = Ro_m \sin(Ao_m)$$

$$Fio = Fio_m$$

and respectively the components of the error-covariance matrix are:

$$S_x0 = [\cos(Ao_m)]\, S_R + [Ro_m \sin(Ao_m)]\, S_A$$

$$S_Y0 = [\sin(Ao_m)]\, S_R + [Ro_m \cos(Ao_m)]\, S_A$$

$$S_{Fi}0 = S_{Fi}$$

The initial values of the other part of the state vector and error-covariance matrix is shown in Table III and was obtained from the apriori information.

The discrete time interval is 1 s.

Table III.

	Value	Variance (So)	Units
Velocity	40	2	m/s
Wind:			
X-component	0	20	m/s
Y-component	0	20	m/s
Turn coefficient:			
Right	0.35	0.165	1/s
Left	0.35	0.165	1/s
K_{Dx}	0	0.00076	1/s
K_{Dy}	0	0.00076	1/s
K_{Hx}	0	0.0042	1/s
K_{Hy}	0	0.0042	1/s

Comparing trajectories of the vehicles which are controlled using the developed algorithm and without it, which are depicted in Fig. 2, it can be observed that the accuracy of control for the

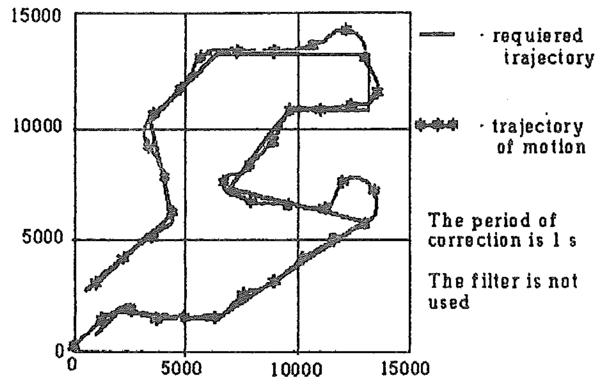

Figure 2.

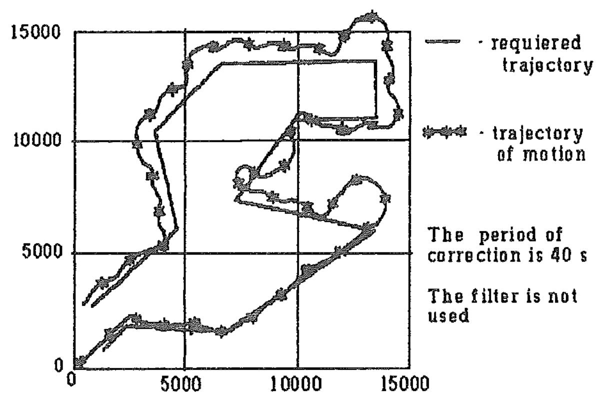

Figure 3.

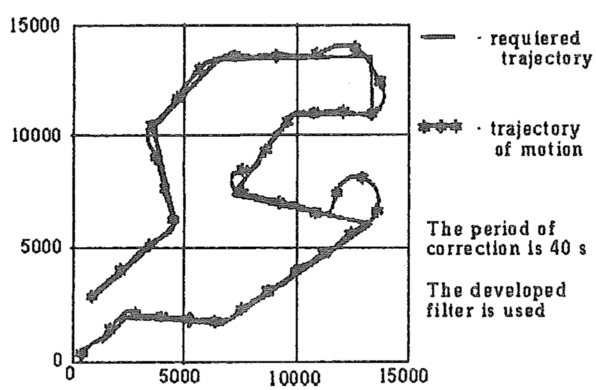

Figure 4.

case where the adaptive filter is used and the period of correction is 40 s is almost the same as for the case where the filter is absent and the period of correction is 1 s. So, if the time of capture of the ground center radar system is 5 s, eight remotely-piloted vehicles could be controlled by one control center. Generally, it depend on the required accuracy of control and the number of vehicles in the system what period of correction to choose.

Conclusions.

The adaptive tracking algorithm is developed and the problem of reducing the number of the ground control centers to operate a lot of remotely-piloted vehicles is solved. Assuming little prior information about the unknown error covariances, the algorithm adaptively adjusts the weights for the best filtering of the inaccurate measurement sequences provided by the ground and on-board sensors. The effectiveness of the algorithm has been demonstrated by the example.

The software developed can be used as an instrument of a designer and also for analyzing the control quality of flight vehicles of a given class.

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