An Application of Firefly Hybrid Extended Kalman Filter Tracking a Reentry Object

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Abstract

Several mathematical models are used for tracking reentry objects in case of radar and sonar. Bayes law evaluations by Unseen Markov Mannequin is one of these which can be used with compatible Kalman filters. To reduce linearization errors, in metaheuristic methods, a new algorithm is proposed by combination of stochastic and metaheuristic techniques. For determination of estimation performance, Firefly Hybrid Extended Kalman Filter has been suggested. Convergence of such systems of firefly is quite high. These are compatible with nonlinear multimodal issues. Simulations studies have been done by MATLAB. The drag resistance is found to be related not only to speed but also to maximum cross sectional errors. The minimization of errors of altitude, velocity and ballistic coefficients are taken to be random. In comparison with Extended Kalman Filter and Hybrid Extended Kalman Filter, the results show 30 to 50 percent error reduction. Combinations of metaheuristic and stochastic methods have immense possibility of development of optimization in case of tracking of reentry objects.

Keywords: Ballistic Coefficient, Extended Kalman Filter, Firefly algorithm, Hybrid Extended Kalman Filter, Metaheuristic, Reentry objects

1. Introduction

Object target path and exposure is a dynamic research area which has attracted extensive attentions from multi-penalizing fields, it has extensive applications in navigation fields like in radars, sonar and military systems. Tracking of falling object into earth re-entry phase. Algorithms are also applied in many Bayesian filter techniques in Gaussian random process. Until now, the underlying mathematical items of most direction in finding ways are Bayes law evaluation and Unseen Markov Mannequin (UMM). Essentially the trendiest systems to predict discrete likelihood distribution are Kalman filter, strengthening extended Kalman filter and mean shift. Kalman filter has the equal thought with UMM, whilst Kalman filter offers with linear. Researchers anticipated specific noise units in the recursion, gathering for extraordinary sign processing approaches; nevertheless those assumptions are stylish on varied purposes and have to be tuned carefully. The significance of optimization is discovering a parameters to makes a superior answer.

For stochastic algorithms, commonly now we have two types: heuristic and metaheuristic. Character-inspired metaheuristic algorithms are apt strong in solving optimization problems. All met heuristic algorithms use special tradeoff a randomization and regional search. Stochastic algorithms mainly have a deterministic aspect and a random factor. The stochastic aspect be capable of acquire many varieties reminiscent of easy randomization through randomly sampling through random walks. Randomization supplies an effective technique to move away from neighborhood investigates.

2. Firefly Algorithm

For illustration, Firefly algorithm is developed by means
of the Xin-She Yang suggests its superiority over some average algorithms Firefly algorithm is encouraged by way of fireflies in nature\(^1\). Fireflies in nature are in a position of producing light owing toward particular luciferase (cell) based dreadfully secure to the physique facade at the back a window of see-through cuticle. Firefly (hotaru) algorithm has some drawback corresponding to trapping into a number of nearby best possible. FA do nearby search as well and mostly can’t acquire exonerate of them. FA constrains are lay down fixed and they do not alternate by using the factor\(^2\). Furthermore FA does not memorize any historical past of bigger hindrance for each firefly and this motives they switch regardless of it, and they also cross over their instances. The procedure of fire fly algorithm in table 1.

Advantages of hotarus algorithm
1. Hotarus can be concerned for enormously non –linear, multi-modal optimization issues naturally and efficiency.
2. Hotarus does now use velocities, and there’s no concern as that related to velocity in PSO.
3. The speed of convergence of hotarus is very high in chance of finding the worldwide optimized answer.
4. It has the pliability of integration with other optimization systems to kind hybrid instruments\(^3,4\).

It does no longer require a just right initial solution to start its iteration approach. Altitude (A), Velocity (V), Ballistic Coefficient (BC), Taylor Series (TS).

The estimate of the states of the non linear procedure as extended the LKF to instantly guessimate the states of nonlinear process referred to as EKF, is certainly the most spacious used nonlinear state evaluation technique that has been practical past few decades. In this paper introduced the new algorithm which is combination of both stochastic and metaheuristic technique is worn to unravel the optimization problem. The new approach algorithm which provides the ways to reduce the linearization errors (altitude, velocity and beta coefficient) that are inherent in the EKF in tracking a target in one dimensional re entry object. The performance firefly hybrid extended Kalman filter FHEKF as estimation performance better results than the EKF.

3. Mathematical Formulation

Kalman filter premise to estimate the derivations of the sate from anostensible state value. Deriving the LKF continuous time of wide-ranging nonlinear system representation. Assuming the ostensible system reentry object as\(^5\)

\[
m = f(m, a, b, t) \\
n = g(m, b, t) \\
o \sim (0, Q) \\
p \sim (0, R) 
\]

The formulation of the right state and right measurement from the ostensible state derivative measurement as

\[
m_0 = f(m_0, a_0, b_0, t) \\
n_0 = g(m_0, c_0, t) \\
\Delta m = m - m_0 \\
\Delta n_0 = n - n_0
\]

The ostensible reentry object, in which case the TS linearization should be approximately correct. The TS linearization of equation 1 represents

\[
m = \tau(m_0, a_0, b_0, t) + \frac{\partial \tau}{\partial m}(m - m_0) + \frac{\partial \tau}{\partial a}(a - a_0) + \frac{\partial \tau}{\partial b}(b - b_0) + \tau(m_0, a_0, b_0, t) + A \Delta m + B \Delta a + L \Delta b \\
n = \gamma(m_0, b_0, t) + \frac{\partial \gamma}{\partial m}(m - m_0) + \frac{\partial \gamma}{\partial c}(c - c_0) + \gamma(m_0, b_0, t) + C \Delta m + B \Delta a + M \Delta b
\]

Partial derivatives matrices evaluated at the ostensible reentry object values

\[
A = \frac{\partial f}{\partial m}|_0 \\
L = \frac{\partial f}{\partial n}|_0 \\
C = \frac{\partial h}{\partial m}|_0 \\
M = \frac{\partial h}{\partial b}|_0
\]

with definitions equations 3 becomes

\[
\Delta \bar{m} = A \Delta m + L \bar{w} \\
\bar{w} \sim (0, \bar{Q}), \bar{Q} = L Q L^T
\]
\[ \Delta n = C \Delta m + Mv \]
\[ \Delta n = C \Delta m + \bar{v} \]
\[ \bar{v} \sim (0, \bar{R}), \bar{R} = \text{MRM}^T \]  
\[ (6) \]

From equation 5 and 6 compute the following matrices

\[ \bar{Q} = \text{LQL}^T \]
\[ \bar{R} = \text{MRM}^T \]  
\[ (7) \]

Define \( \Delta n \) as the differentiation involving the definite measurement \( n \) and the titular measurement \( n_0 \)

\[ \Delta n = n - n_0 \]  
\[ (8) \]

The input to the sieve consist of \( \Delta n \), observing the variation among the genuine extent \( n \) and the titular extent \( n_0 \). The Kalman filter is a guess estimate of the variation among the genuine state \( m \) and the ostensible state \( m_0 \).

\[ \Delta \dot{m}(0) = 0 \]
\[ P(0) = \text{E}[(\Delta m(0) - \Delta \dot{m}(0))(\Delta m(0) - \Delta \dot{m}(0))^T)] \]
\[ \Delta \dot{m} = A \Delta m + K(\Delta y - C \Delta \dot{m}) \]
\[ K = PC^T \bar{R}^{-1} \]
\[ \dot{P} = AP + PA^T + \bar{Q} - PC^T \bar{R}^{-1} CP \]
\[ \dot{m} = m_0 + \Delta \dot{m} \]  
\[ (9) \]

coalesce the \( m_0 \) expression in equation 2 with the \( \Delta \dot{m} \) equation 9 to obtain

\[ \dot{m}_0 + \Delta \dot{m} = f(m_0, a_0, b_0, t) + A \Delta \dot{m} + K \begin{bmatrix} n \end{bmatrix} \]  
\[ (10) \]

The ostensible measurement expression in equation 2 becomes

\[ n_0 = g(m_0, c_0, t) \]
\[ = g(\dot{m}, c_0, t) \]  
\[ (11) \]

And equation 10 becomes

\[ \dot{m} = f(m_0, a_0, b_0, t) + K[n - g(\dot{m}, c_0, t)] \]  
\[ (12) \]

Where \( K \) represented as Kalman gain, the titular noise values are prearranged as \( b_0 = 0 \) and \( c_0 = 0 \). These equations additionally will also be articulate in nonlinear state area type as a suite of first order nonlinear differential equations. If \( x \) is the distance from the radar to the object

\[ \ddot{x} = \text{Drag} - g = \frac{Q_p g}{\dot{a}} - g \]  
\[ (13) \]

Where \( \beta \) is the ballistic coefficient of the item. Bear in mind that the BC, which is regard as to be a consistent in this quandary, the amount of drag performing on the reentry object. Assumed that \( b \) used to be known upfront. The dynamic strain \( Q_p \) within the preceding equation is given through

\[ Q_p = 0.5 \rho \dot{x}^2 \]  
\[ (14) \]

The place \( \rho \) is the air density. We will nonetheless expect air compactness is an opponent function of altitude

\[ \rho = 0.0034 e^{-x/22000} \]  
\[ (15) \]

the nonlinear second-order differential equation

\[ \dot{s} = \frac{Q_p g}{\beta} - g = 0.5 \rho \dot{s}^2 g - g = \frac{0.0034 e^{-x/22000} s^2 g}{2\beta} - g \]  
\[ (16) \]

for the reason that the BC of the object route is unknown, it can put together in a state. Fundamental to estimate the \( A, V, BC \) of the thing in an effort to route it. As a result, the state equation for the proposed filter are given through

\[ \begin{bmatrix} s \\ \dot{s} \\ \beta \end{bmatrix} = \begin{bmatrix} \dot{s} \\ 0 \\ 0 \end{bmatrix} \]  
\[ (17) \]

a nonlinear perform of the state equation according to

\[ \dot{s} = 0.0034 e^{-x/22000} s^2 g - g \]  
\[ (18) \]

Moreover, the BC is constant, that means its sequel have got to be zero

\[ \beta = 0 \]  
\[ (19) \]

Adding a system noise to the derivative of the BC becomes

\[ \dot{\beta} = u_s \]  
\[ (20) \]

where \( u_s \) is white system noise.
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the partial derivatives are evaluated on the present state equation guesstimates. The linearized state equation is continuous approach noise matrix is given below

\[
\frac{\partial \hat{s}}{\partial \beta} = \left\{ \begin{array}{ccc}
\frac{\partial \hat{s}}{\partial s} & \frac{\partial \hat{s}}{\partial s} & \frac{\partial \hat{s}}{\partial \beta} \\
\frac{\partial \hat{s}}{\partial \beta} & \frac{\partial \hat{s}}{\partial \beta} & \frac{\partial \hat{s}}{\partial \beta} \\
\frac{\partial \hat{\beta}}{\partial \beta} & \frac{\partial \hat{\beta}}{\partial \beta} & \frac{\partial \hat{\beta}}{\partial \beta}
\end{array} \right\} \Delta s + \Delta \hat{\beta}
\]

(21)

\[
F(t) = \begin{bmatrix}
0.0034 & 0 & 0 \\
-\rho \hat{s}^2 g / (44000 \hat{\beta}) & \rho \hat{s} g / \hat{\beta} & -\rho \hat{s}^2 g / 2 \hat{\beta}
\end{bmatrix}
\]

(22)

\[
\rho = 0.0034 e^{-22000}
\]

\[
F(t) = \begin{bmatrix}
f_1 & f_2 & f_3 \\
0 & 0 & 0
\end{bmatrix}
\]

(23)

Let \( \hat{\beta}_0 = 0.0034 \) and \( k = 22000 \) then the continuous time EKF to estimate the A, V and BC of a reentry object as it falling.

\[
m_0 = \begin{bmatrix} 100,000 & -6000 & 2500 \end{bmatrix}^T
\]

(24)

By considering all the above, the Fitness function can be formulated is as follows

\[
\text{Cost} = \min (\text{MSE})
\]

where

\[
\text{MSE} = (F_2^2 - F_1^2)^{1/2}
\]

(25)

Table 1. Pseudo code for firefly algorithm

| Procedure FFA Metaheuristic () |
|--------------------------------|
| Begin:                       |
| Initialize algorithm constraints: |
| \( n \): the quantity of fires \|
| \( \gamma \): the radiance absorption coefficient \|
| \( \beta_0 \): initial attractiveness at \( r = 0 \) \|
| \( \alpha \): the randomization limit of movement \|
| Generate the preliminary population of movement; |
| Define the target function of \( f(x) \); |
| Investigate the radiance moderation of \( f(x) \); |
| While (stopping criterion no longer met) |
| For \( i = 1 \) to \( n \) (all \( n \) hotaru); |
| For \( j = 1 \) to \( n \) (\( n \) hotaru) |
| If \( I_j > I_i \), move firefly \( I \) towards \( j \); |
| End if; |
| Gorgeous varies with distance \( r \) via \( \text{Exp}[-\gamma r^2] \); |
| Appraise new solutions and update light intensity; |
| End for \( j \); |
| Rank the \( n \) hotaru and locate the up to date finest; |
| End while; |
| Post progression outcomes and visualization; |
| End procedure; |

Table 2. Error parameter estimation for different filters

| Parameters        | EKF     | HEKF    | FHEKF   |
|-------------------|---------|---------|---------|
| Altitude          | 32.0812 | 25.8851 | 17.0136 |
| Velocity          | 18.1543 | 15.9174 | 13.5883 |
| Ballistic coefficient | 183.9866 | 254.9092 | 0.0085191 |
| Best solution     | 5.0182  | 2.8851  | 0.0795  |
4. Simulation Results and Analyzing

According to the above analysis, the resistance is not only related to the speed, but also the maximum cross-sectional area on the air resistance. Set an observer, we observed the state motion of the falling objects, deriving from observations into the HEKF filter, and then calculate the estimate of motion state. The performance of the firefly hybrid extended Kalman filter is evaluated using MATLAB. The simulation results of one dimensional object tracking applied in this scenario. The parameters of altitude, velocity, ballistic coefficient are compared for EKF, HEKF and FHEKF. In terms of altitude errors, FHEKF has less 50 percent over EKF and 30 percent over HEKF shown in table 1.2. Similarly for velocity errors it has greater minimization effect. Comparing the figure 1 and figure 2 of A, V, BC variation in altitude is gradually increase from -10 to 10 in HEKF but in FHEKF increases -10 to 0 similarly in velocity it decrease from 100 to 2 with some variations in HEKF but in FHEKF decrease 100 to 1 gradually decreasing without any variations also in BC it more varying with some noise HEKF but FHEKF as get constant variation from -500 and slightly increasing to 0 without any distributions. The ballistic coefficient has a slightly different pattern of variation. However the best solution is obtained with FHEKF.

6. Conclusion

This paper has combined metaheuristic and stochastic method for the purpose of error minimization in the parameters like altitude, velocity and ballistic coefficient. In compression with EKF and HEKF the results are quite spectacular. This method is likely to be given popularity in applications of reentry object in sonar and radar.
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