

Dynamic Data Processing with Kalman Filter

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Introduction

Adaptive information processing methods are widely used for data processing. Most often they are used for two or more sensor information complex processing. In navigation GPS information is most often complex treated with inertial sensor information using adaptive filtering techniques [2,3]. If navigation system has only one source of information, adaptive filtering can be used [1, 4]. Widely known are following algorithms: Least Mean Square (LMS) algorithm, Recursive Least Squares (RLS) algorithm and Kalman Filtering (KF) algorithm. Results of research Least Square Method (LSM) for one source information filtering with sliding window are shown in [1]. This work describes results of Kalman filter modeling and optimization and usage of adaptive Kalman filter for GPS information processing. Comparison of data processing results with adaptive Kalman filter and Least Square Method (LSM) with sliding window is shown.

Modeling of data processing with two component Kalman filter

Trajectory of mobile object movement is supposed to be linear with radical change in one point. We modeling true coordinate in point i or in time t_i using expression (1). All modeling values are relative, velocity is a relative coordinate change in the time step between two points

$$xt_i = x_0 + V_x i, \quad (1)$$

where x_0 is coordinate in starting point, but V_x is velocity of x coordinate change.

Maximal object movement dynamic is if velocity changes from positive to negative or contrary. In Fig. 1 is shown true coordinate time function, if linear movement and radical change of 180° are used for mobile object trajectory modeling. True trajectory measurement errors e_i are modeling as normal process with mean value M_e equal zero and root square value - σ_e . In Fig. 1 are shown true trajectory with error $Y_i = xt_i + e_i$ modeling when $\sigma_e=2$. Y_i is measured trajectory Y_i .

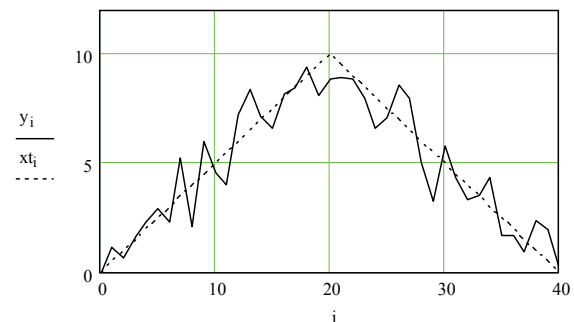


Fig. 1. True coordinate x_{t_i} changing model if $x_0=0, V_x=0.5$ and changes to $V_x=-0.5$ and measure value Y_i when errors are modeling with $M_e=0, \sigma_e=2$

Measured coordinate x_{m_i} and velocity of coordinate change are estimated using two measuring devices: first determinate coordinate, for example positioning system GPS and second determinate velocity, for example using accelerometers. In this case Kalman filtering algorithms must be use for estimation of mobile object movement trajectory x_e :

$$\begin{cases} Ra_x = Rx + Sx, \\ Kx = \frac{Ra_x}{(Ra_x + Sxm)}, \\ xe = Ra_x + Ve + Kx (xm - xe - V), \\ Rx = Ra_x - Kx Ra_x \end{cases} \quad (2)$$

and velocity V_e :

$$\begin{cases} RaV = RV + SV, \\ KV = \frac{RaV}{(RaV + SVM)}, \\ Ve = Ve + KV (Bm - V), \\ RV = RaV - KV RaV, \end{cases} \quad (3)$$

where Sx and SV spectral density of object trajectory and velocity fluctuation, Rx and RV – covariance of the

coordinate and velocity estimation error, R_{ax} and R_{aV} predict covariance of the coordinate and velocity estimation error, K_x and K_V Kalman filter transfer function,

Modeling results of trajectory estimation using Kalman filter, when $S_x = S_V = 0$, $\sigma_e = 2$, $R_{x_0} = 4$ and $R_{V_0} = 0.3$ are shown in Fig. 2 and Fig. 3.

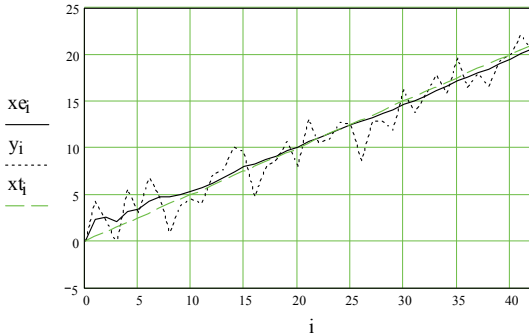


Fig. 2. Trajectory estimation results with two measuring devices and Kalman filtering, when $S_x = S_V = 0$

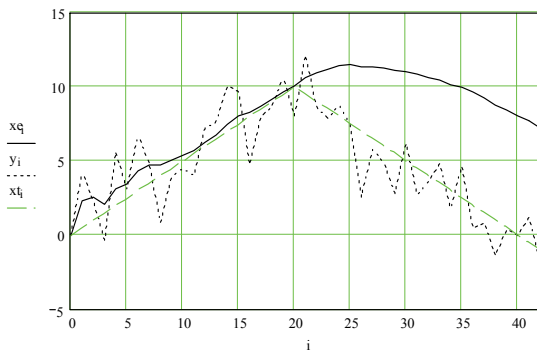


Fig. 3. Trajectory estimation results with two measuring devices and Kalman filtering and velocity change in point $i=20$ from $+0.5$ to -0.5 , $S_x = S_V = 0$

How it is seen from Fig. 2 estimation results is good, if coordinate change is linear. When velocity changes (Fig. 3) estimation error has very high value beginning with velocity changing point. To decrease dynamic errors often use Kalman filtering with some artificial object fluctuation [4]. So we modeling filtering process using $S_x = 0.02$ and $S_V = 0.02$. Results are shown in Fig. 4. How it can be seen dynamic error decrease, but modeling results also show that the estimation error in this case grow, for example in Fig. 4 it is two times more. Value of artificial object fluctuation can be chosen for every dynamical object individual, using optimization method of static and dynamic errors.

Another method is method with we use for adaptive filtering with sliding window [1]. In this method when estimated and measure trajectory value difference is more than same constant, the parameters of Kalman filter is change. We research Kalman filter adaptation when measure value of trajectory Y_i coordinate and estimated coordinate x_{e_i} difference is more than σ_e

$$|Y_i - x_{e_i}| \geq \sigma_e \quad (4)$$

When equation (4) is true then filter transfer functions are set $K_i = K_V = 1$ and filter values are so $V_i = 0$ and $x_{e_i} = x_{m_i}$.

Results of modeling so adaptive Kalman filter with two measuring devices and velocity change in point $i=20$ from $+0.5$ to -0.5 , $S_x = S_V = 0$ is shown in Fig. 5. Filter adaptation is done in point $i=25$, when difference between estimation and measuring error is more than $\sigma_e = 2$.

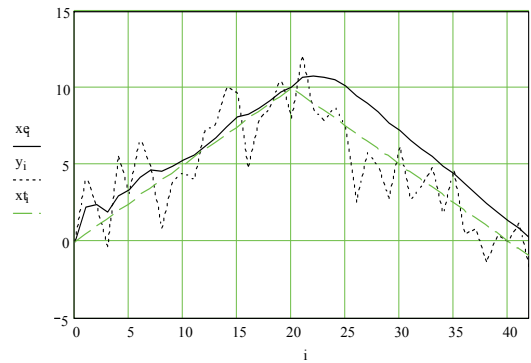


Fig.4 Trajectory estimation results with two measuring devices and Kalman filtering and velocity change in point $i=20$ from $+0.5$ to -0.5 , $S_x = S_V = 0.02$

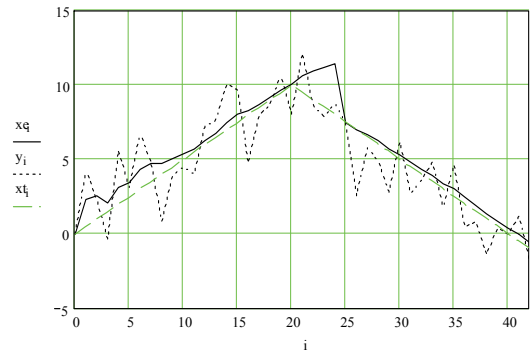


Fig. 5. Trajectory estimation results with two measuring devices and adaptive Kalman filtering and velocity change in point $i=20$ from $+0.5$ to -0.5 , $S_x = S_V = 0$, adaptation in point $i=25$, when estimation and measuring error difference is more than $\sigma_e = 2$

How can see from Fig. 5 coordinate x_e estimation error is small and and estimated trajectory is very closed to real trajectory x_t which is modeling.

This method can be used also in case when velocity measuring device have offset

$$V_m = V + \Delta V \quad (5)$$

In this case Kalman filtering give growing estimation error as it is shown in Fig. 6.

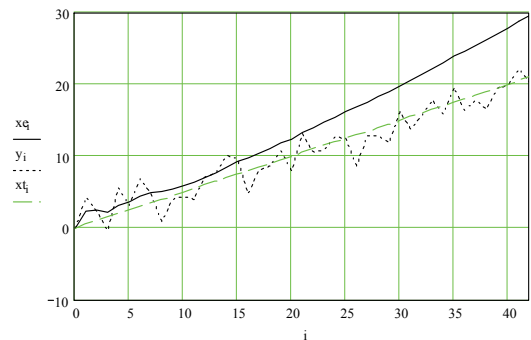


Fig. 6. Trajectory estimation results with two measuring devices and Kalman filtering when velocity measuring device have offset $\Delta V = 0.04$

When adaptive Kalman filter with condition (4) for parameter correction is used offset effect can be decrease Fig. 7.

Described method for offset correction can be used, but better is employ third equation in Kalman filter for determination of the offset.

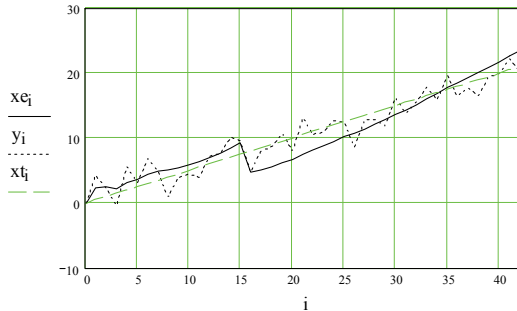


Fig. 7. Trajectory estimation results with two measuring devices and Kalman filtering when velocity measuring device have offset $\Delta V=0.04$ and in point $i=16$ is make filter parameter correction

Modeling of data processing with Kalman filter if one measuring device is used for trajectory and velocity measuring

When one device is used, velocity can be processing from coordinate measuring results using Kalman filter or some another filter. If Kalman filter is used, velocity V_e processing equations are following:

$$\begin{cases} RaV = RV + SV, \\ KV = \frac{RaV}{(RaV + SVM)}, \\ Ve = Ve + KV(xm - xe - V), \\ RV = RaV - KV RaV. \end{cases} \quad (6)$$

Fig. 8. shows modeling results when one device measurements are process with Kalman filter using (2) and (6) and mobile object trajectory change in point $i=20$.

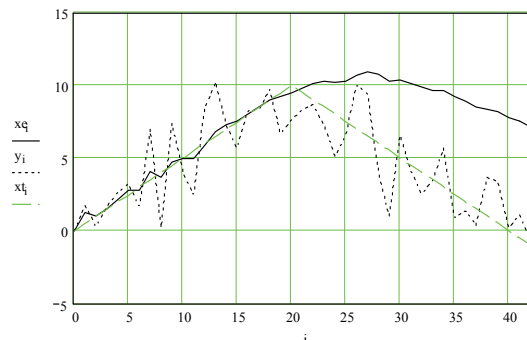


Fig. 8. Trajectory estimation results with one measuring devices and Kalman filtering and velocity change in point $i=20$ from $+0.5$ to -0.5 , $S_x = S_V = 0$

In this case also dynamic error is very large and we must use adaptive Kalman filtering. If filter adaptation with condition (4) is used, modeling error decrease (Fig. 9).

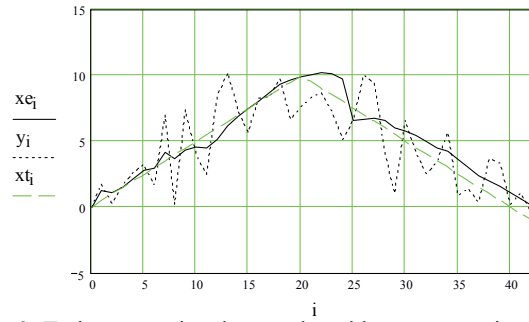


Fig. 9. Trajectory estimation results with one measuring devices and Kalman filtering and velocity change in point $i=20$ from $+0.5$ to -0.5 , $S_x = S_V = 0$, in point $i=25$ filter parameters are corrected

GPS data filtering with adaptive Kalman filter

Next step is to use the adaptive Kalman filter for some fragment of GPS data processing. There are 4 turns in this data fragment [1]. Fig. 10 shows measured data (x_m) and estimated data (x_e) processing with Kalman filter.

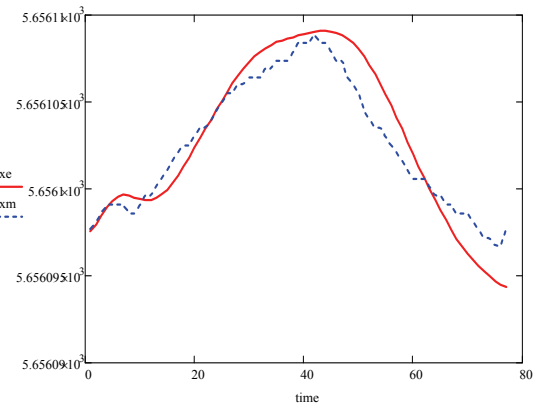


Fig. 10. GPS data processing results with Kalman filter.

Filtering gives quite significant error in turns. Estimation results using adaptive Kalman filter are shown in Fig. 11. As shown in the Fig. 11 result of data filtering is much better.

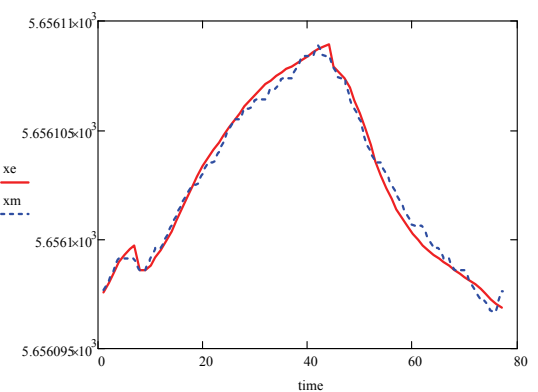


Fig. 11. GPS data processing results with adaptive Kalman filter

Comparison results of GPS date filtering with LMS algorithm [1] shows that Kalman adaptive filter gives better results for filtering dates in short time interval.

Conclusions

This work describes results of adaptive Kalman filter modeling for dynamic data processing when two or one source of information is used. Also adaptive Kalman filter algorithms are used for GPS information processing.

Results of modeling mobile object trajectory detection, using adaptive Kalman filter, that estimation error decrease if mobile object parameters change very rapidly. Expressions for Kalman filter parameter change are developed. Adaptive Kalman filter estimation is used for GPS data filtering and shows that modeling results is equal real data filtering.

References

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In this work research results of dynamic data processing with adaptive Kalman filter are presented. In filtering process parameters of filter are change on results of difference between measuring and expected coordinate. Modeling results of adaptive Kalman filtering are comparing with classic Kalman filter. Modeling results using adaptive Kalman filtering for coordinate estimation shows that estimation error decrease in points when parameters of movement change very rapidly. Results of adaptive Kalman filter modeling and filter use for GPS receiver information processing are described. III. 11, bibl. 4 (in English; abstracts in English and Lithuanian).

A. Kluga, J. Kluga. Kalmano filtrų matavimo dinaminį rezultatų apdorojimas // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2011. – Nr. 5(111). – P. 33–36.

Pateikiami Kalmano filtrų dinaminio apdorojimo rezultatai gauti jų parametrus keičiant matuojamos ir apskaičiuotos koordinatės skirtumo dydžiu. Klasikinio filtro duomenys lyginami su adaptyviųjų filtrų modeliavimo duomenimis. Nustatyta, kad paklaida gerokai sumažėja greitai keičiantis judesio parametrus. Pateikiami realaus GPS imtuvo tyrimo duomenys. II. 11, bibl. 4 (anglų kalba; santraukos anglų ir lietuvių k.).