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EFFECTIVE DETECTION OF STRONG MANEUVERS OF OBJECT IN NOISY MEASUREMENTS CONDITIONS

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Abstract. In this paper coordinate measurements of the object, which trajectory includes strong maneuvers, are used as input data. Strong maneuvers described here as fast turns of the object in sharp angles. Measurement data are very noisy, and standard filtration methods (Kalman filter) don't give satisfactory results. In this paper an improved filtration method that is capable to detect strong maneuvers effectively was implemented. The filtration algorithm was applied to multirotor UAV's tracking task.

Keywords: UAV, DSP, Kalman filter, trajectory analisys.

1. Introduction

The Kalman filter is widely used in engineering tasks: from radar and object tracking systems [1-4] to prediction of weather [5], [6] and neural networks training [7], [8]. However, to meet the requirements of accuracy and timeliness of detecting a moving object, the standard method of filtering measurements with the Kalman filter requires further work. The specifics of the Kalman filter application for the tasks of tracking the moving object are described in the work [9]. The dynamic tracking algorithm (in real time conditions) behind the object moving at a constant speed is described in the article [10].

2. Problem description

The main goal of the work is implementing an effective and reliable moving object tracking algorithm capable to detect strong maneuvers. Position of the object to be tracked is defined by noisy measurements. Further an example of coordinates measurements of an object performing strong maneuver is provided. On the Fig. 1

blue line describes object's coordinate measurements, while red line curve stands for filtered trajectory.

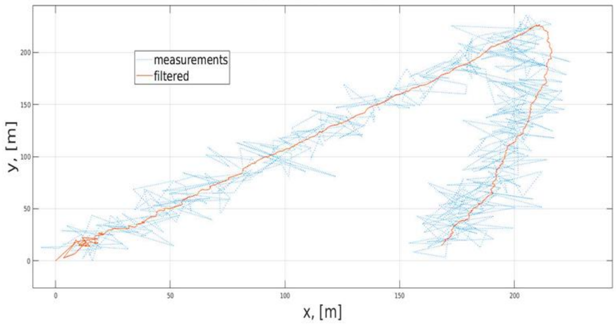

Fig. 1. UAV trajectory in Cartesian coordinates.

The filtration in this case was performed using Kalman filter. Next equations describe the motion model of the object:

$$x_i = x_{i-1} + v_{i-1}^x T + \frac{a_{i-1}^x T^2}{2} \quad (1)$$

$$v_i^x = v_{i-1}^x + a_{i-1}^x T \quad (2)$$

$$y_i = y_{i-1} + v_{i-1}^y T + \frac{a_{i-1}^y T^2}{2} \quad (3)$$

$$v_i^y = v_{i-1}^y + a_{i-1}^y T \quad (4)$$

Where time step is T=1. In addition, initial conditions are as follows: X_0 is a state vector at start movement time, $P_{0,0}$ – initial covariance matrix that determines the error value of initial state guess and X_i a state vector of the system:

$$X_0 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, P_{0,0} = \begin{bmatrix} 10^5 & 0 & 0 & 0 \\ 0 & 10^5 & 0 & 0 \\ 0 & 0 & 10^5 & 0 \\ 0 & 0 & 0 & 10^5 \end{bmatrix}, X_i = \begin{bmatrix} x_i \\ v_i^x \\ y_i \\ v_i^y \end{bmatrix} \quad (5)$$

However, standard filtration methods lead to significant detection error at the time of the sharp direction change, which is illustrated on the Fig. 1. Therefore, the filtration method optimization problem appears in order to increase reliability of object's strong maneuvers detection.

3. Solution algorithm

The residual between Kalman filter outcomes and measurements is defined as the value: $v_i = z_i - HX_{i,i-1}$. Fig. 2 and Fig. 3 illustrate the time dependence of values v_i, $i=x,y$.

On Fig. 2 and Fig. 3 the red lines represent the same residuals but smoothed using running mean algorithm. The graphs above are characterized by significant change in the residual value during the period of strong maneuver (this fact is shown better at the v_y-evolution graph).

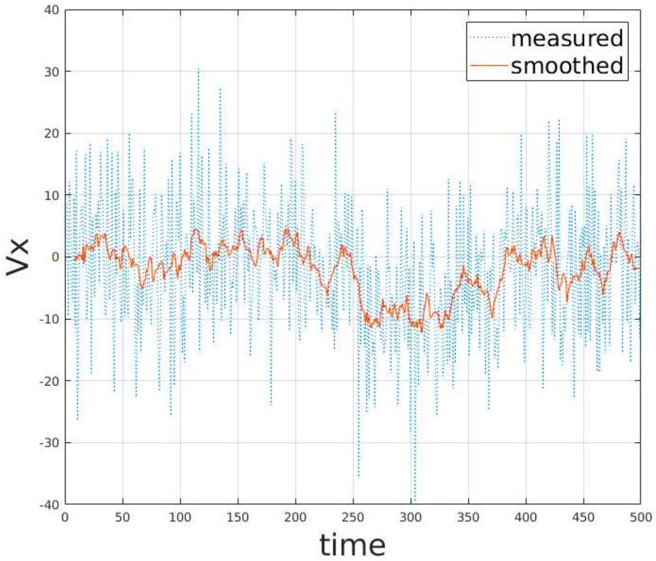

Fig. 2. Residuals of deviation errors along the X-axis.

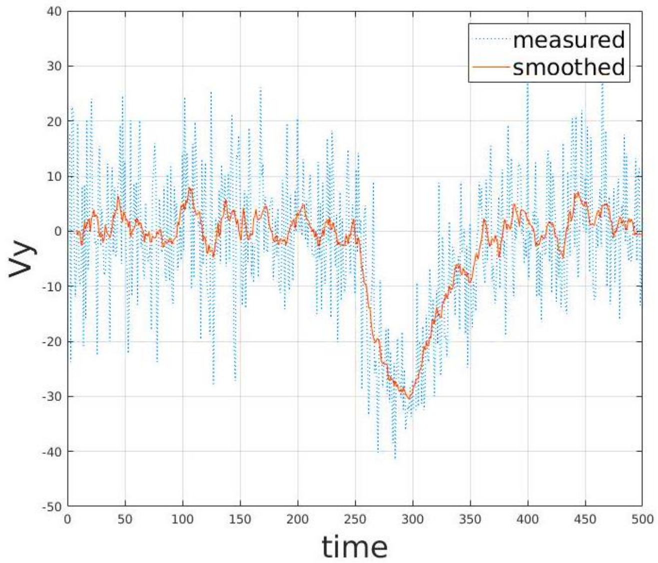

Fig. 3. Residuals of deviation errors along the Y-axis.

It is obvious that for successful filtration of measurements the residuals errors v_i should not exceed errors of measurements $\sigma_i, i = x, y$. As soon as the value v_i exceeds the threshold, the choice of which is determined by the measurement error, the moment of sharp turn is detected. In this case, the Kalman filter is reinitialized with a set of initial parameters. Thus, the modified Kalman filter after the change of direction of movement generates new values, leaning more on subsequent measurements, than previous results of filtration. If the filter is not reinitialized, its algorithm will provide values based on the previous results of filtration, for which the residual value of v_i is large. The equations (6-9) describe the software implementation of this algorithm.

$$V = Z - HX_{i,i-1} \tag{6}$$

$$if\ v_x > scale * \sigma_N\ or\ v_y > scale * \sigma_N \tag{7}$$

$$then\ \ P_{f\,j_i} = \begin{bmatrix} 10^5 & 0 & 0 & 0 \\ 0 & 10^5 & 0 & 0 \\ 0 & 0 & 10^5 & 0 \\ 0 & 0 & 0 & 10^5 \end{bmatrix} \tag{8}$$

$$else\ P_{f\,j_i} = \left(\begin{bmatrix} 10^5 & 0 & 0 & 0 \\ 0 & 10^5 & 0 & 0 \\ 0 & 0 & 10^5 & 0 \\ 0 & 0 & 0 & 10^5 \end{bmatrix} - K_i H \right) P_{pr_i} \tag{9}$$

Further we evaluate *scale* value graphically. On one chart we'll define absolute values of smoothed residuals v_i, $, i = x, y$ and determine the minimum value of the scale constant, fixing a significant change of the smoothed values v_i, $, i = x, y$, see. Fig. 4.

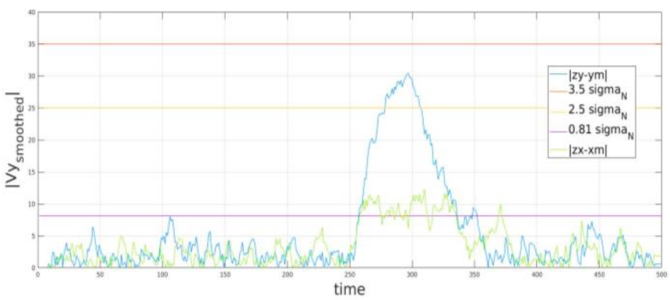

Fig. 4. Graphical estimation of the *scale* value.

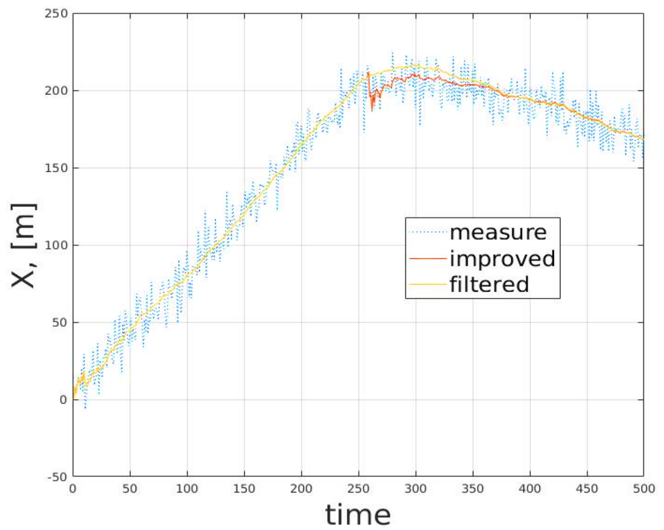

Fig. 5. Filtration results in X-axis separately.

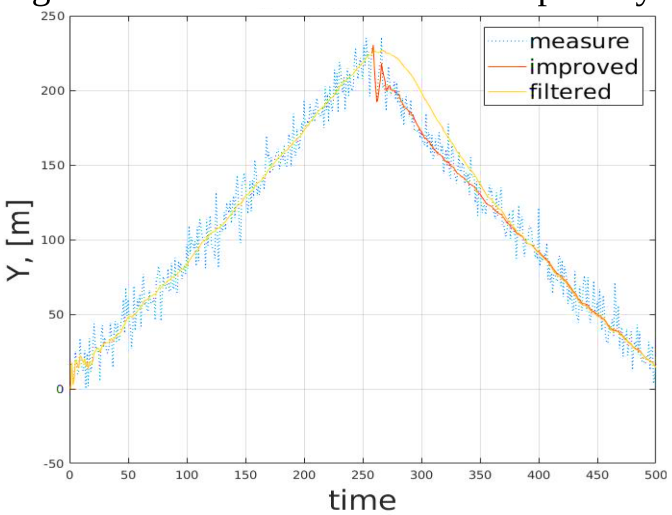

Fig. 6. Filtration results in Y-axis separately

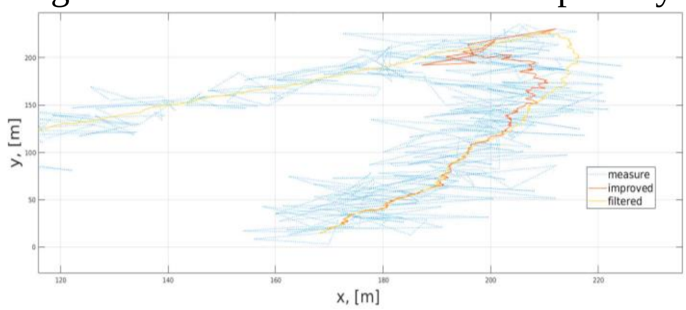

Fig. 7. Modified Kalman filter algorithm results in XY-plane

In this case, it is wise to choose the value of *scale* = 0.81, highlighting the moment of the turn from the noise level. After application of this approach for filtration of noisy measurements we get significant improvement in terms of timely detection of sharp maneuver of the object. The results of the algorithm are presented on the Fig. 5-7, where blue dots represent measurements, the yellow line shows the results of the operation of the standard Kalman filter, the red line shows an improved filtering algorithm for the task of detecting a sudden change in direction of motion.

4. Results of the application of the filtering algorithm

Consider the results of the modified filtration algorithm applied to the trajectories of multiritor type UAV, Quadrocopter. These small drones are widely used due to their maneuverability, capable of performing many sharp turns in a short period of time. That is why the trajectories of the drones are particularly interesting in terms of the object tracking task.

We analyze the test trajectory specified by a series of randomly selected control points. Fig. 8-10 show the measurements, the real and the two variants of the filtered drone trajectories in the projections for each space axis. The measurement error in this case is 0.1 m. The algorithm that tracks the abrupt changes in the direction of movement shows the best result than filtering with the unmodified Kalman filter.

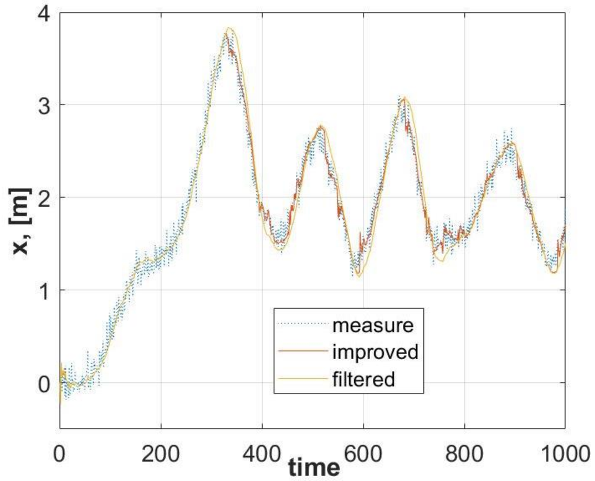

Fig. 8. Comparison of filtering algorithms along X-coordinate

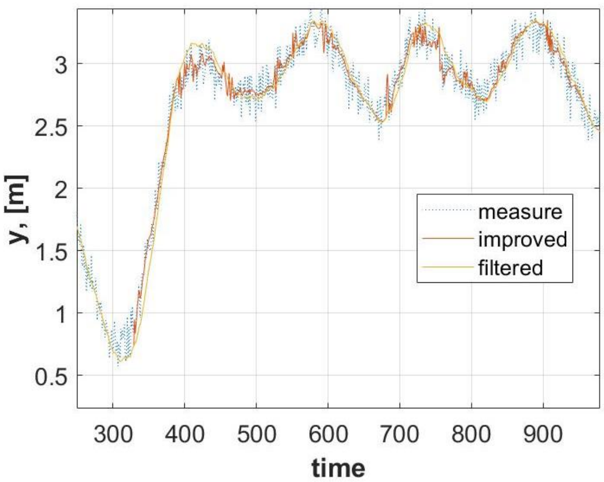

Fig. 9. Comparison of filtering algorithms along Y-coordinate

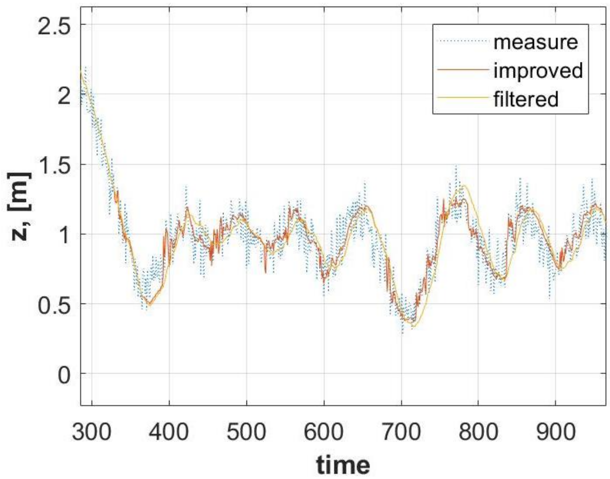

Fig. 10. Comparison of filtering algorithms along Z-coordinate.

Here is a numerical comparison of the proposed filtration method for sharp maneuvers detection with the algorithm of unmodified Kalman filter. For this purpose, we shall consider mean square errors of deviation of the obtained trajectories in comparison with real ones for each one-dimensional coordinate, see. Fig. 11.

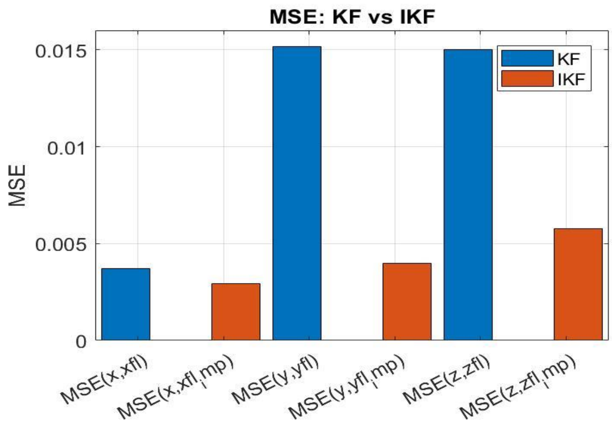

Fig. 11. Comparison of root-mean-square errors along X, Y, Z coordinates

The modified filtration algorithm provides a much more accurate tracking result of the UAV at x and y coordinates, which is consistent with the visual representation shown in Fig. 8-10.

To compare the work of the modified algorithm Kalman on the trajectories of a real drone. The error of measurements of the UAV trajectory was 5 m. The results of modified algorithm for trajectory filtering of the real UAV are presented on Fig.12 and Fig.13.

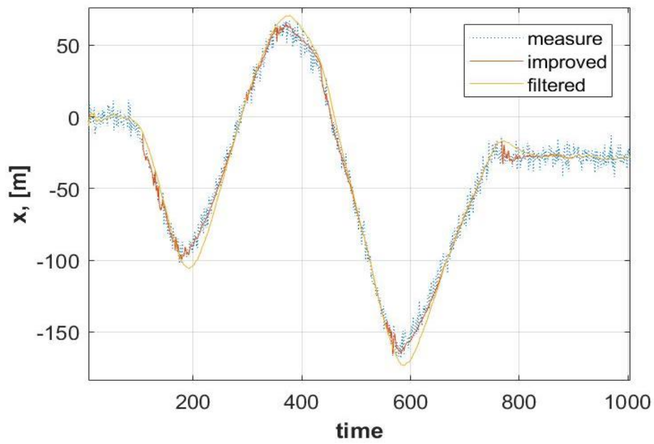

Fig. 12. Trajectory filtering of the real UAV along X-axis

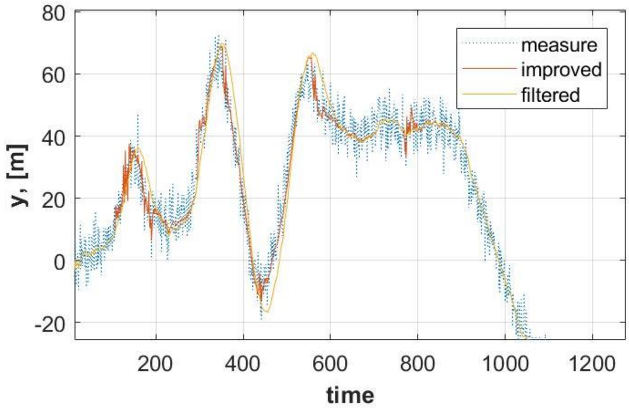

Fig. 13. Trajectory filtering of the real UAV along Y-axis

5. Conclusion

In the paper the algorithm of tracking of the object performing sharp maneuvers is considered on the basis of filtration of noisy measurements. The proposed tracking algorithm is a modification of the Kalman filter. The performance of this method is estimated on the example of multirotor UAV trajectory. Its comparative analysis with the unmodified filter Kalman is conducted, the proposed algorithm showed greater accuracy. The modified algorithm is also used to filter the trajectory of the real UAV.

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