Infinite Science | Publishing

On the use of an extended Kalman filter for subviral particle tracking

A. Rausch[1*] and T. Schanze[1]

[1] *Institute of Biomedical Engineering (IBMT), Faculty of Life Science Engineering (LSE), Technische Hochschule Mittelhessen (THM) – University of Applied Sciences, Gießen, Germany*
[*] *Corresponding author, email: andreas.rausch@lse.thm.de*

Abstract: The ongoing outbreaks of the Ebola disease in the Democratic Republic of Congo demand a faster medical reaction. To accelerate the search for an antiviral, processes need to be automated. Previously, algorithms to automatically detect, track and analyze subviral particles in fluoroscopic image sequences were presented. Thereby, a linear Kalman filter algorithm is used to improve the tracking. In this publication the predictions of the linear and an extended Kalman filter are compared. Both approaches are tested on a real subviral particle track and show that an extended Kalman filter is suitable for the complex motion patterns of subviral particles.

I. Introduction

The ongoing outbreaks of the Ebola virus cause a high death toll. By the rapidly increasing globalization there also is a certain danger for a pandemic spread of this disease. To stop the current epidemic and to prevent a possible global outbreak the research for an antiviral medicine must be accelerated. The research for antivirals requires a profound knowledge of the pathogens. Therefore, a high number of infected cells need to be analyzed.

In cooperation with the Institute of Virology, Philipps-University, Marburg, algorithms for an automated analysis of subviral particles in fluorescence microscopy image sequences were developed. Attention was spent to the analysis of the motion patterns of the subviral particles [1, 2, 3]. This demands an accurate detection- and tracking-algorithm. Thereby, a big challenge is to design a tracking algorithm that is robust against image noise, low contrast and overlapping structures. Especially the latter can cause big interruptions within a track. To enable a high-quality statistical evaluation of the particle motion these interruptions have to avoided. Good results were achieved with a previously published linear Kalman filter-based algorithm [4].

As subviral particles have a highly nonlinear behavior [5], there are still some cases in which the linear Kalman filter (LKF) is not suitable, like reconstructing a gap that is interrupted within a curved section. In this publication the benefits of an extended Kalman filter (EKF) with a nonlinear motion model are investigated [6]. Both, the EKF (new) and LKF (old) are tested on a real subviral particle track to compare their ability in reconstructing data within measurement-gaps.

The results show a similar accuracy for both methods (EKF and LKF). The article ends with a Discussion sections.

II. Material and methods

This section starts with the presentation of the applied Kalman filter. The testing data is presented which are a real subviral particle track from a fluorescence microscopy image sequence.

II.I. Extended Kalman filter model

A Kalman filter can predict the state of a system based on the previous measurements. Thus, it can be used for two aspects: 1st it can estimate the current state and thus compensate temporal absence of measurements; 2nd the estimation can be used to correct the current measurement which results in the Kalman's filter-characteristic.

The EKF can be divided into two steps:

1st Predict

$$\tilde{s}_k = g_A(s_{k-1}) \tag{1}$$
$$\tilde{P}_k = J_A P_{k-1} J_A^T + Q \tag{2}$$

2nd Correct

$$K_k = \tilde{P}_k J_H^T (J_H \tilde{P}_k J_H^T + R)^{-1} \tag{3}$$
$$s_k = \tilde{s}_k + K_k(z_k - g_H(\tilde{s}_k)) \tag{4}$$
$$P_k = (I - K_k J_H)\tilde{P}_k, \tag{5}$$

with s, the state vector; g_A, the nonlinear model matrix; P, the covariance matrix; $J_{A,H}$, the Jacobi matrices of the model A and measurement vector H; Q and R, the process and measurement noise matrices; I, unit matrix; K, the Kalman gain; and z, the current measurement. s and P are the corrected versions of the predicted $\tilde{s}$ and $\tilde{P}$. [6]

While the common Kalman filter relies on a linear motion model with constant velocity, the EKF can depict nonlinear models in its model matrix (Eq. 1). A Constant Turn Rate and Velocity (CTRV) model in polar domain was chosen [7]. The state vector s is given by:

$$s = [x, y, \Phi, v, \omega]^T \quad (6)$$

The system states in s correspond to:

$$g(s) = \begin{bmatrix} \frac{v}{\omega}(sin(\omega T + \Phi) - sin(\Phi)) + x \\ \frac{v}{\omega}(-cos(\omega T + \Phi) + cos(\Phi)) + y \\ \omega T + \Phi \\ v \\ \omega \end{bmatrix} \quad (7)$$

The tracking algorithm detects the positions x and y of the subviral particles. Thus, the measurement matrix is:

$$H = [1,1,0,0,0]^T \quad (8)$$

II.II. Gap reconstruction

The EKF is applied to one subviral particle track, detected using the previously presented algorithm [4]. The track has a complex motion pattern, which has been perfectly detected. (Fig. 1). To test the prediction capability of the EKF, the track is interrupted by a gap with a duration of five frames – five measurements are missing. The gap successively “slides” over each track position (Fig. 1, grey box).

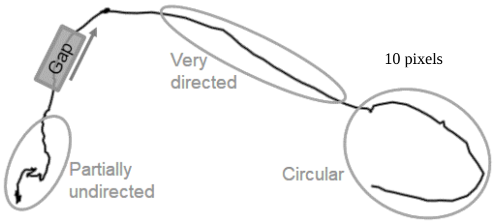

Figure 1: Subviral particle track: A real subviral particle track with various motion patterns (ellipses) is analyzed. To test the gap-closing performance of the LKF/EKF a gap-window subsequently slides over all track positions.

The EKF is applied to the whole track for each gap-position. Thereby, it is applied in forward and backward direction, as there is no need for a real-time application (e.g. [4]). The mean square error between LKF- and EKF-prediction and original track within the gap area is measured. Thereby, the gap-closing performance of the LKF/EKF is tested for each motion pattern.

III. Results and discussion

The filtering and prediction quality of an EKF with CTRV-model is tested on a real subviral particle track.

III.I. Gap reconstruction

Fig. 2 shows that the prediction of the new EKF and old LKF have similar results. Both can reconstruct interrupted tracks with a small deviation to the original track (mean EKF: 0.60; mean LKF: 0.53). This enables a high grade of data reconstruction in case of insufficient tracking caused by inadequate image quality with both Filters.

IV. Conclusions

The advantage of applying an EKF were evaluated. The ability of reconstructing lost data is a huge advantage for the automated analysis of subviral particles in often highly noisy image data. Both, the LKF and EKF work similar accurate. The filters’ accuracy profits especially by the

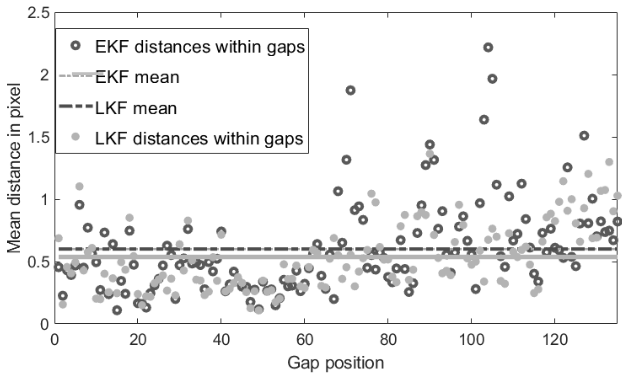

Figure 2: Gap reconstruction: A sliding gap-window is applied to the track in Fig. 1. The mean distances between original track and the prediction $\tilde{s}$ of EKF (black) / LKF (grey) within the produced gaps are shown in relation to the gap position (averages: lines in corresponding colors). The mean distance between original track and EKF correction s is shown for the same positions (black).

forward and backward processing of the track. In future work, evaluating the turn-rate model parameter ω of the EKF could help understanding and describing the subviral particles’ motion behavior. Other motion models should be considered as they may match the subviral particle behavior more than the CTRV-model. Thereby, the initial parameters to set up the EKF should be also further investigated.

ACKNOWLEDGMENTS

We want to thank the workgroup of Stephan Becker at the Institute of Virology, Philipps-University, Marburg, for the great cooperation and supply with image data.

AUTHOR’S STATEMENT

Research funding: The author state no funding involved. Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study.

REFERENCES

[1] A. Rausch, T. Schanze, *Fractal Dimensions of Subviral Particles Motion*, Current Directions in Biomedical Engineerung, Vol. 4, 2018.

[2] A. Rausch, T. Schanze, *Sliding Fractal Dimensions of Subviral Particle Movement, Biomedical Journal of Scientific and Technical Research*, Vol. 6, Issue 2, 2018.

[3] A. Rausch, T. Schanze, *Fractal Characterization of Subviral Particle Motion: On the Influence of Spatio-Temporal Interpolation Methods*, 41st Annual International Conference of the IEEE in EMBC, 2019, IEEE Xplore, pp. 6012-6017.

[4] A. Rausch, D. Müller, T. Schanze, *Improvement of a subviral particle tracker by the use of a LAP-Kalman-algorithm*, Current Directions in Biomedical Engineerung, Vol. 2, 2016.

[5] G. Schudt, O. Dolnik, L. Kolesnikova, N. Biedenkopf, A. Herwig, S. Becker, *Transport of Ebolavirus Nucleocapsids Is Dependent on Actin Polymerization: Live-Cell Imaging Analysis of Ebolavirus-Infected Cells*, The Journal of Infectious Diseases, Vol. 212, Issue suppl. 2, 2015, pp. 160-166.

[6] Q. Li, R. Li, K. Ji, W. Dai, *Kalman Filter and Its Application*, 8th International Conference of Intelligent Networks and Intelligent Systems, 2015, pp. 74-77.

[7] M. Roth, F. Gustafson, EKF/UKF, *EKF/UKF Maneuvering Target Tracking using Coordinated Turn Models with Polar/Cartesian Velocity*, 8th International Conference of Intelligent Networks and Intelligent Systems, 2015, pp. 74-77.