ERP Estimation using a Kalman Filter in VLBI

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Abstract Geodetic Very Long Baseline Interferometry (VLBI) is one of the primary space geodetic techniques, providing the full set of Earth Orientation Parameters (EOP), and it is unique for observing long term Universal Time (UT1). For applications such as satellite-based navigation and positioning, accurate and continuous ERP obtained in near real-time are essential. They also allow the precise tracking of interplanetary spacecraft. One of the goals of VGOS (VLBI Global Observing System) is to provide such near real-time ERP. With the launch of this next generation VLBI system, the International VLBI Service for Geodesy and Astrometry (IVS) increased its efforts not only to reach 1 mm accuracy on a global scale but also to reduce the time span between the collection of VLBI observations and the availability of the final results substantially. Project VLBI-ART contributes to these objectives by implementing an elaborate Kalman filter, which represents a perfect tool for analyzing VLBI data in quasi real-time. The goal is to implement it in the GFZ version of the Vienna VLBI Software (VieVS) as a completely automated tool, i.e., with no need for human interaction. Here we present the methodology and first results of Kalman filtered EOP from VLBI data.

Keywords VGOS, Kalman filter, EOP

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1 Introduction

At the moment the VLBI products have a latency of about two weeks. However, as the need for near real-time estimates of the parameters is increasing, e.g., for satellite based navigation and positioning or for enabling precise tracking of interplanetary spacecraft [Ichikawa et al., 2004], the efforts to shorten the time span between observation and final results have been increased considerably. To reach these goals, the VLBI Global Observing System (VGOS; Petrachenko et al. [2009]) was proposed, where a dense network of very fast moving antennas (slewing speed $>6°$/s) is foreseen, providing a high number of observations per time unit. The aim is to reach an accuracy of 1 mm (position) and 1 mm/year (velocity) from a global solution of 24-hour sessions, and near real-time operation with the help of electronic data transfer to the correlators. In order to retrieve the analysis results in near real-time, a solution algorithm applying completely automated processes is also required. One way to achieve these goals is by implementing an adaptive Kalman filter in place of the classical least-squares method (LSM) in VLBI analysis software packages. Herring et al. [1990] had proposed such an approach already in the 1990s, where the clock and atmosphere parameters are modeled as stochastic processes, which can authentically represent the geodetic parameters as well as the dynamics of the system processes. Various software packages include such a Kalman filter approach, e.g., Occam [Titov et al., 2004]. However, the existing software packages implemented the Kalman filter in the form of a post-processing tool, as at that time continuous VLBI observations were utopistic and VLBI was not designed for true real-time applications. Within project VLBI-ART, a Kalman filter will be realized that is in particular designed for analyzing VLBI data in (near) real-time. This method has the advantage that simultaneously both the deterministic estimation of parameters, which usually change slowly throughout time, e.g., station positions, and the tracking of highly variable parameters showing a stochastic behavior, like clocks or atmospheric parameters, are possible. The filter is able to perform the VLBI parameter estimation without any manual interaction, making it a completely autonomous tool. In this paper we describe the filter and discuss its application for ERP determination.

2 Mathematical Principle of a Kalman Filter in VLBI

Traditional VLBI analysis software uses the least-squares method (LSM) or least-squares collocation for the estimation of the desired parameters, in which most of the parameters showing a stochastic behavior, such as clock and atmospheric disturbance, are approximated by piecewise linear functions. The length and order of these polynomials have to be chosen manually by the analyst according to session type and duration and may vary from analyst to analyst, and thus they are subjective. For this method, the observations have to be artificially bundled as they cannot handle a continuous data flow. All this hinders the efficiency of the data processing and makes a continuous data analysis almost impossible.

The Kalman filter was especially developed for real-time applications and is widely applied in various fields of research and development including the analysis of space geodetic data (cf. Herring et al. [1990]; Morabito et al. [1988]; Nilsson et al. [2011]). The advantage of such a filter over ordinary least-squares is that the estimation is carried out sequentially, epoch by epoch, by combining the observations at each time step with the estimation of the previous ones, making it ideal for real-time applications [Kalman, 1960]. Further, stochastic models replace the polynomial parameter models and thus more appropriately describe the physics behind the processes.

The Kalman filter should follow the sequence of observations, using the state at the epoch $(t-1)$ to predict the state at the next epoch t. Finally the predicted value is combined with the new information to get an optimal estimation for t. If $\mathbf{x}_t$ is the state vector containing all unknown parameters to be estimated at epoch t, it can be related to the estimates at a previous epoch $\mathbf{x}_{t-1}$ through

$$\mathbf{x}_t = \mathbf{F}_t \mathbf{x}_{t-1} + \mathbf{w}_t \ , \tag{1}$$

where $\mathbf{F}_t \mathbf{x}_{t-1}$ is the prediction of $\mathbf{x}_t$ based on $\mathbf{x}_{t-1}$ and $\mathbf{w}_t$ is the error in the prediction. $\mathbf{F}$ is called the state transition matrix. The covariance matrix of the total error $\mathbf{P}_t^-$ can be calculated by

$$\mathbf{P}_t^- = \mathbf{F}_t \mathbf{P}_{t-1} \mathbf{F}_t^T + \mathbf{Q}_t \ , \tag{2}$$

with $\mathbf{P}_{t-1}$ denoting the variance-covariance matrix of $\mathbf{x}_{t-1}$ and $\mathbf{Q}_t$ the variance-covariance matrix of the prediction error $\mathbf{w}_t$. The observations $\mathbf{z}_t$ at epoch t are introduced through

$$\mathbf{z}_t = \mathbf{H}_t \mathbf{x}_t + \mathbf{v}_t \ . \tag{3}$$

$\mathbf{H}_t$ is the observation matrix and $\mathbf{v}_t$ is the observation noise. To get the optimal estimation for $\mathbf{x}_t$ and its covariance matrix $\mathbf{P}_t$ the prediction $\mathbf{x}_t^-$ and the observation $\mathbf{z}_t$ can be combined using

$$\mathbf{x}_t = \mathbf{x}_t^- + \mathbf{K}_t (\mathbf{z}_t - \mathbf{H} x_t^-) \ , \mathbf{P}_t = (\mathbf{I} - \mathbf{K}_t \mathbf{H}_t) \mathbf{P}_t^- \ , \tag{4}$$

with the Kalman gain $\mathbf{K}_t$

$$\mathbf{K}_t = \mathbf{P}_t^- \mathbf{H}_t^T (\mathbf{H}_t \mathbf{P}_t^- \mathbf{H}_t^T + \mathbf{R}_t)^{-1} \ , \tag{5}$$

where $\mathbf{R}_t$ is the variance-covariance matrix of the observation noise $\mathbf{v}_t$.

In our filter the state transition matrix $\mathbf{F}$ is realized as a unit matrix with the dimensions $[n \times n]$ with n being the number of unknowns. Since all the deterministic models are already applied within VieVS [Böhm et al., 2012], only the stochastic processes are left to be modeled. Exceptions are the clock parameters, where the relationship between offset and rate is described through a parameter of the primary diagonal. The noise parameters for the process noise covariance matrix $\mathbf{Q}$ are taken from literature (e.g., [Herring et al., 1990]). For the clock, these noise parameters were determined empirically. The observation matrix $\mathbf{H}$ consists of the partial derivatives of the delay w.r.t. the unknowns. For most cases these are identical to the ones used in the LSM approach.

3 First Results

Here first results of session 08JUN19XE_N004 are shown. We chose this session as it represents an average state-of-the-art IVS VLBI session and falls into the time span where ERPs from GPS [Steigenberger et al., 2006] are available to us. It involved seven antennas and contains 1,576 observations within 596 scans over 24 hours. The filter was set up to estimate x- and y-pole, dUT1, station coordinates, and zenith wet delays for all stations, as well as clock and clock rate for all stations except the reference clock. Here, only the results for polar motion and dUT1 are shown (Figure 1).

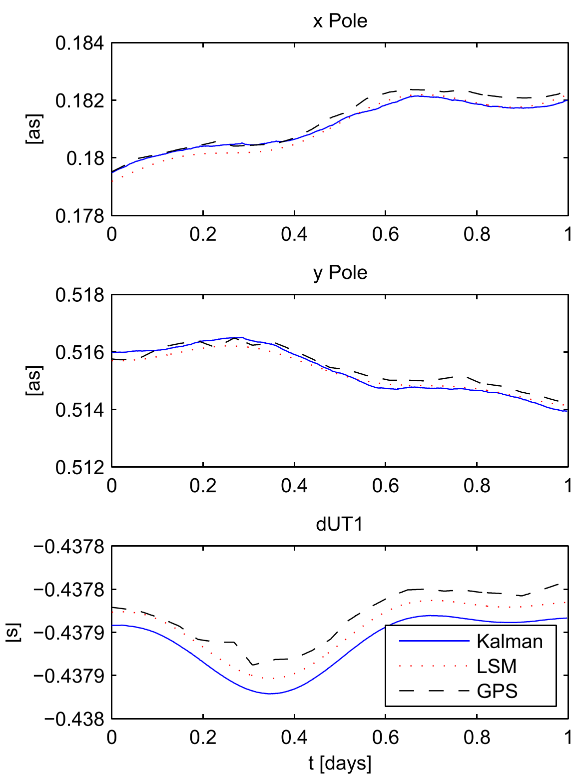

Fig. 1 The upper plot shows x-pole, the middle shows y-pole, and the lower shows dUT1. The solid graph depicts the results for the Kalman filter, the dotted line shows the results for the LSM solution, and the dashed line shows the GPS parameters.

Although the noise parameters were chosen independently of the LSM solution, i.e., no tuning towards the LSM solution was performed, the results show a very good agreement. The adjustments to the IERS 08 C04 [Bizouard et al., 2009] a priori of dUT1 differ at the microsecond level. See Table 1 for RMS values of the various approaches. For an external validation, an ERP time series derived from GPS was used. Because not all the models involved in the determination are known, only the final ERP series can be compared. In spite of biases, the agreement is good, although the differences in general are larger in comparison to the LSM solution. For y-pole the Kalman solution agrees slightly better with the GPS results. Further investigations are needed and other sessions have to be chosen to verify these results, as also the GPS time series show some small unexpected peaks (see Figure 1).

Table 1 RMS of the three solutions, i.e., Kalman (KAL) and LSM in comparison to the GPS time series.

	RMS KAL adjustments only	RMS (KAL–LSM) adjustments only
x-pole [μas]	0.2152	0.1834
y-pole [μas]	0.1347	0.1796
dUT1 [ms]	0.0135	0.0176
	RMS (LSM–GPS) a priori included	**RMS (KAL–GPS) a priori included**
x-pole [mas]	0.2778	0.3235
y-pole [mas]	0.2187	0.1488
dUT1 [ms]	0.0154	0.0325

4 Current Status and Outlook

A first version of the Kalman filter was implemented and is now in the debugging phase. We showed preliminary results for the ERP and compared them to the classical LSM, and we found a very good agreement. The comparison of Kalman filter with GPS also shows a good agreement between the results. All results are still under investigation and validation, as well as the GPS time series itself, as it shows some unexpected peaks. Further, the clock models will be improved, so that clock breaks are automatically detected. This is the first step towards full automation. Later the filter will be extended to other parameters such as source coordinates or station velocities. The improvement of the system dynamics and the fine tuning of the process noise as well as the refinement of the deterministic and stochastic models are ongoing as well. We plan to have the filter fully operational for the analysis of the CONT14 campaign.

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