



# On the stability of the continuous-time Kalman filter subject to exponentially decaying perturbations



Daniel Viegas<sup>a,\*</sup>, Pedro Batista<sup>b</sup>, Paulo Oliveira<sup>b,c</sup>, Carlos Silvestre<sup>a,1</sup>

<sup>a</sup> Department of Electrical and Computer Engineering, Faculty of Science and Technology, University of Macau, Taipa, Macau

<sup>b</sup> Institute for Systems and Robotics, Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal

<sup>c</sup> IDMEC, Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal

## ARTICLE INFO

### Article history:

Received 11 June 2015

Accepted 27 October 2015

Available online 8 January 2016

### Keywords:

Kalman filtering

Estimation

Time-varying systems

## ABSTRACT

This paper details the stability analysis of the continuous-time Kalman filter dynamics for linear time-varying systems subject to exponentially decaying perturbations. It is assumed that estimates of the input, output, and matrices of the system are available, but subject to unknown perturbations which decay exponentially with time. It is shown that if the nominal system is uniformly completely observable and uniformly completely controllable, and if the state, input, and matrices of the system are bounded, then the Kalman filter built using the perturbed estimates is a suitable state observer for the nominal system, featuring exponentially convergent error dynamics.

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## 1. Introduction

This paper details the stability analysis of the continuous-time Kalman filter subject to exponentially decaying perturbations in the input, output, and matrices of the system. The topic of state estimation subject to perturbations in the dynamics of the system has been extensively covered in the framework of robust estimation for uncertain systems, see e.g. [1] and [2]. Existing research on the subject ranges from results on quadratically stable linear time-invariant systems, see e.g. [3–5], to more general approaches on generic linear time-varying (LTV) systems such as in [6] and [7]. More recently, works such as [8–10] proposed robust filtering solutions for cases in which the matrices of the nominal system are uncertain, but known to reside in a given convex polytope. While the above-cited references consider mostly norm-bounded uncertainties, this paper considers exponentially decaying perturbations. Although this class of signals is admittedly more restrictive, it allows for arbitrarily large initial values for the uncertainties, as well as recovering the optimal Kalman filter dynamics

in steady state. Another difference with respect to the existing literature regards the prior knowledge of the nominal system: while some works assume that the dynamics of the nominal system are known and others admit that they reside in a given polytope, in this paper the filter is implemented without knowing the nominal system dynamics, using instead estimates of the system matrices corrupted by the aforementioned unknown perturbations. This formulation is useful for analysis of interconnected Kalman filters in a cascade setup. While there are a number of stability results for cascade systems (see e.g. [11]), interconnecting time-varying Kalman filters in such a fashion introduces additional problems, as the estimation error of the first filter in the cascade might inject exponentially decaying errors in the dynamics of the other filters at several levels: in the input, the output, the matrices of the system model, and the computation of the filter gain and error covariance matrix. For a practical application of the results detailed in this paper, see e.g. [12], in which autonomous vehicles working in formation use state estimates from other agents to compute the system matrices needed to implement local Kalman filters. The above-cited paper includes a simplified version of the results detailed in this paper, which considers perturbations only in the input  $\mathbf{u}(t)$  and output matrix  $\mathbf{C}(t)$ . In comparison, in this paper perturbations are introduced in most matrices of the system model (with the exception of the noise covariances  $\mathbf{Q}(t)$  and  $\mathbf{R}(t)$ ) as well as both the input and output of the system. As a result of this, the results detailed here are more general but also more complex, for the most part due to the perturbation in  $\mathbf{A}(t)$  which induces errors in the state transition matrix  $\Phi(t, t_0)$ .

\* Correspondence to: Room E11-2038, Faculty of Science and Technology, University of Macau, Taipa, Macau.

E-mail addresses: [dviagas@isr.ist.utl.pt](mailto:dviagas@isr.ist.utl.pt) (D. Viegas), [pmatista@isr.tecnico.ulisboa.pt](mailto:pmatista@isr.tecnico.ulisboa.pt) (P. Batista), [pjcro@isr.ist.utl.pt](mailto:pjcro@isr.ist.utl.pt) (P. Oliveira), [csilvestre@umac.mo](mailto:csilvestre@umac.mo) (C. Silvestre).

<sup>1</sup> On leave from Instituto Superior Técnico/University of Lisbon, 1049-001 Lisbon, Portugal.

The rest of the paper is organized as follows. Section 2 details the problem at hand as well as the assumptions required to derive the results in subsequent sections. A generic LTV system is considered, and it is assumed that estimates of the input, output, and matrices of the system are available to implement the Kalman filter, but subject to unknown perturbations which decay exponentially with time. The two following sections detail auxiliary results which are necessary to derive the main result of this paper: in Section 3, it is shown that if the nominal system is uniformly completely observable (UCO) and uniformly completely controllable (UCC), then the perturbed system is also UCO and UCC; and in Section 4, it is shown that the solution of the Riccati equation for the Kalman filter built with the perturbed parameters converges exponentially fast to the solution of the Riccati equation for the nominal Kalman filter. Section 5 details the main result of this paper: using the previous results, it is shown that the perturbed version of the Kalman filter constitutes a suitable state observer for the nominal LTV system, featuring error dynamics that converge exponentially fast to zero. Finally, Section 6 summarizes the main conclusions of this work.

### 1.1. Notation

Throughout the paper the symbol  $\mathbf{0}$  denotes a matrix (or vector) of zeros and  $\mathbf{I}$  an identity matrix, both of appropriate dimensions. For a matrix  $\mathbf{A}$ ,  $\|\mathbf{A}\|$  denotes its induced 2-norm, and  $\|\mathbf{A}\|_F$  denotes its Frobenius norm. The notation  $\text{vec}(\mathbf{A})$  denotes the vectorizing operator, which returns a vector constructed by stacking the columns of the matrix  $\mathbf{A}$ . For a symmetric matrix  $\mathbf{P}$ ,  $\mathbf{P} > \mathbf{0}$  and  $\mathbf{P} \geq \mathbf{0}$  indicate that  $\mathbf{P}$  is positive definite and positive semi-definite, respectively.

## 2. Problem statement

Consider the LTV system

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}(t)\mathbf{u}(t) \\ \mathbf{y}(t) = \mathbf{C}(t)\mathbf{x}(t), \end{cases} \quad \mathbf{x}(t_0) = \mathbf{x}_0, \quad (1)$$

where  $\mathbf{x}(t) \in \mathbb{R}^n$ ,  $\mathbf{u}(t) \in \mathbb{R}^m$ ,  $\mathbf{y}(t) \in \mathbb{R}^o$ , and  $\mathbf{x}_0 \in \mathbb{R}^n$  are the state, input, output, and initial condition of the system, respectively.  $\mathbf{A}(t)$ ,  $\mathbf{B}(t)$ , and  $\mathbf{C}(t)$  are matrix-valued functions of time of appropriate dimensions. To simplify the notation throughout the text, from hereon time-dependency of the variables is not explicitly shown ( $\mathbf{x}$  is used instead of  $\mathbf{x}(t)$ , for example). In general, all functions and variables that appear in the text should be treated as time-varying unless explicitly stated otherwise.

It is assumed that all quantities in (1) are bounded for all time, that is, there exist positive scalar constants  $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ , and  $\alpha_5$  such that

$$\begin{cases} \|\mathbf{x}\| \leq \alpha_1 \\ \|\mathbf{u}\| \leq \alpha_2 \end{cases} \quad \text{and} \quad \begin{cases} \|\mathbf{A}\| \leq \alpha_3 \\ \|\mathbf{B}\| \leq \alpha_4 \\ \|\mathbf{C}\| \leq \alpha_5 \end{cases} \quad (2)$$

for all  $t \geq t_0$ .

The dynamics of the continuous-time Kalman filter for (1) follow

$$\begin{cases} \dot{\hat{\mathbf{x}}} = \hat{\mathbf{A}}\hat{\mathbf{x}} + \hat{\mathbf{B}}\mathbf{u} + \hat{\mathbf{K}}[\mathbf{y} - \hat{\mathbf{C}}\hat{\mathbf{x}}] \\ \hat{\mathbf{K}} = \hat{\mathbf{P}}\hat{\mathbf{C}}^T\hat{\mathbf{R}}^{-1} \\ \dot{\hat{\mathbf{P}}} = \hat{\mathbf{A}}\hat{\mathbf{P}} + \hat{\mathbf{P}}\hat{\mathbf{A}}^T + \hat{\mathbf{D}}\hat{\mathbf{Q}}\hat{\mathbf{D}}^T - \hat{\mathbf{P}}\hat{\mathbf{C}}^T\hat{\mathbf{R}}^{-1}\hat{\mathbf{C}}\hat{\mathbf{P}}, \end{cases} \quad \begin{cases} \hat{\mathbf{x}}(t_0) = \hat{\mathbf{x}}_0 \\ \hat{\mathbf{P}}(t_0) = \hat{\mathbf{P}}_0, \end{cases} \quad (3)$$

in which  $\hat{\mathbf{x}} \in \mathbb{R}^n$  is the state estimate of the filter,  $\hat{\mathbf{K}} \in \mathbb{R}^{n \times o}$  is the filter gain, and  $\hat{\mathbf{P}} > \mathbf{0} \in \mathbb{R}^{n \times n}$  is the estimation error covariance matrix.  $\hat{\mathbf{x}}_0$  and  $\hat{\mathbf{P}}_0$  are, respectively, the initial state estimate and initial error covariance matrix. The matrices  $\hat{\mathbf{D}} \in \mathbb{R}^{n \times p}$ ,  $\hat{\mathbf{Q}} \geq \mathbf{0} \in \mathbb{R}^{p \times p}$ , and  $\hat{\mathbf{R}} > \mathbf{0} \in \mathbb{R}^{o \times o}$  are used to model process and observation

noise. It is assumed that there exist positive scalar constants  $\alpha_6, \alpha_7$ , and  $\alpha_8$  such that

$$\begin{cases} \|\hat{\mathbf{D}}\| \leq \alpha_6 \\ \alpha_7^{-1} \leq \|\hat{\mathbf{R}}\| \leq \alpha_7 \\ \|\hat{\mathbf{Q}}\| \leq \alpha_8 \end{cases} \quad (4)$$

for all  $t \geq t_0$ .

Now, suppose that for implementation of the Kalman filter (3) the nominal values of  $\mathbf{A}$ ,  $\mathbf{B}$ ,  $\mathbf{C}$ ,  $\mathbf{D}$ ,  $\mathbf{u}$ , and  $\mathbf{y}$  are not available and that estimates of those quantities, denoted respectively as  $\hat{\mathbf{A}}$ ,  $\hat{\mathbf{B}}$ ,  $\hat{\mathbf{C}}$ ,  $\hat{\mathbf{D}}$ ,  $\hat{\mathbf{u}}$ , and  $\hat{\mathbf{y}}$  must be used instead. Define the errors on those estimates as

$$\begin{cases} \tilde{\mathbf{A}} := \mathbf{A} - \hat{\mathbf{A}} \\ \tilde{\mathbf{B}} := \mathbf{B} - \hat{\mathbf{B}} \\ \tilde{\mathbf{C}} := \mathbf{C} - \hat{\mathbf{C}} \\ \tilde{\mathbf{D}} := \mathbf{D} - \hat{\mathbf{D}} \\ \tilde{\mathbf{u}} := \mathbf{u} - \hat{\mathbf{u}} \\ \tilde{\mathbf{y}} := \mathbf{y} - \hat{\mathbf{y}}. \end{cases} \quad (5)$$

It is assumed that these errors decay exponentially fast with time, that is, there exist positive scalar constants  $\alpha_9, \alpha_{10}, \alpha_{11}, \alpha_{12}, \alpha_{13}, \alpha_{14}, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$ , and  $\lambda_6$  such that

$$\begin{cases} \|\tilde{\mathbf{A}}\| \leq \alpha_9 e^{-\lambda_1(t-t_0)} \\ \|\tilde{\mathbf{B}}\| \leq \alpha_{10} e^{-\lambda_2(t-t_0)} \\ \|\tilde{\mathbf{C}}\| \leq \alpha_{11} e^{-\lambda_3(t-t_0)} \\ \|\tilde{\mathbf{D}}\| \leq \alpha_{12} e^{-\lambda_4(t-t_0)} \\ \|\tilde{\mathbf{u}}\| \leq \alpha_{13} e^{-\lambda_5(t-t_0)} \\ \|\tilde{\mathbf{y}}\| \leq \alpha_{14} e^{-\lambda_6(t-t_0)} \end{cases} \quad (6)$$

for all  $t \geq t_0$ . Note that, as a result of the boundedness of  $\mathbf{A}$  and  $\hat{\mathbf{A}}$ , the norm of the associated state transition matrices,  $\Phi(t, t_0)$  and  $\hat{\Phi}(t, t_0)$  respectively, can also be bounded for finite intervals. More specifically, for any given  $T > 0$ , there exist positive scalar constants  $\alpha_{15}$  and  $\alpha_{16}$  such that

$$\begin{cases} \|\Phi(t + t^*, t)\| \leq \alpha_{15} \\ \|\hat{\Phi}(t + t^*, t)\| \leq \alpha_{16} \end{cases} \quad (7)$$

for all  $0 \leq t^* \leq T$  and  $t \geq t_0$ .

Using the estimates that are available, the Kalman filter equations become

$$\begin{cases} \dot{\hat{\mathbf{x}}} = \hat{\mathbf{A}}\hat{\mathbf{x}} + \hat{\mathbf{B}}\mathbf{u} + \hat{\mathbf{K}}[\mathbf{y} - \hat{\mathbf{C}}\hat{\mathbf{x}}] \\ \hat{\mathbf{K}} = \hat{\mathbf{P}}\hat{\mathbf{C}}^T\hat{\mathbf{R}}^{-1} \\ \dot{\hat{\mathbf{P}}} = \hat{\mathbf{A}}\hat{\mathbf{P}} + \hat{\mathbf{P}}\hat{\mathbf{A}}^T + \hat{\mathbf{D}}\hat{\mathbf{Q}}\hat{\mathbf{D}}^T - \hat{\mathbf{P}}\hat{\mathbf{C}}^T\hat{\mathbf{R}}^{-1}\hat{\mathbf{C}}\hat{\mathbf{P}}. \end{cases} \quad (8)$$

Note that, due to the perturbations in the parameters of the system, both the filter gain  $\hat{\mathbf{K}}$  and the solution of the Riccati equation  $\hat{\mathbf{P}}$  will deviate from their nominal counterparts  $\mathbf{K}$  and  $\mathbf{P}$ . The new filter equations (8) will be referred to as Perturbed Kalman Filter (PKF) equations from hereon for the sake of convenience.

The observability Gramian associated with the pair  $(\mathbf{A}, \mathbf{C})$  is defined as

$$\mathcal{W}_o(t_1, t_2) = \int_{t_1}^{t_2} \Phi^T(\sigma, t_1) \mathbf{C}^T(\sigma) \mathbf{R}^{-1}(\sigma) \mathbf{C}(\sigma) \Phi(\sigma, t_1) d\sigma,$$

and the controllability Gramian associated with the pair  $(\mathbf{A}, \mathbf{D})$  follows

$$\mathcal{W}_c(t_1, t_2) = \int_{t_1}^{t_2} \Phi(t_1, \sigma) \mathbf{D}(\sigma) \mathbf{Q}(\sigma) \mathbf{D}^T(\sigma) \Phi^T(t_1, \sigma) d\sigma.$$

The pair  $(\mathbf{A}, \mathbf{C})$  is said to be UCO if and only if there exist positive scalar constants  $\delta_1$  and  $\gamma_1$  such that

$$\gamma_1^{-1} \leq \mathbf{d}^T \mathcal{W}_o(t, t + \delta_1) \mathbf{d} \leq \gamma_1$$

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