Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnline CONFERENCE PAPER ARCHIVE

IFAC-PapersOnLine 49-22 (2016) 274–279

Switching data-processing methods in a control loop: Trade-off between delay and probability of data acquisition

E.P. van Horssen * **D. Antunes** * **W.P.M.H. Heemels** *

* *Control System Technology Group, Eindhoven University of Technology, P.O. Box 513, 5600 MB Eindhoven, The Netherlands, (e-mail: {e.p.v.horssen, d.antunes, w.p.m.h.heemels}@tue.nl).*

Abstract: Many control applications, such as vision-based control, require data-processing methods to distill sensor information. This data-processing introduces several undesired effects in the control loop, such as delays, the probability of not acquiring information, and measurement inaccuracies. Often, these effects obey a trade-off. For example, the probability of acquiring control-relevant information, related to the probability of data-loss, is typically higher if a larger delay is allowed. While a single processing method with a reasonable trade-off is typically selected, we propose instead a solution to switch between data-processing methods with different delays and corresponding data-loss probabilities. We prove that the proposed method achieves a better LQG-type performance when compared to the individual methods. A simulation considering a second-order system illustrates the advantages of the proposed method.

Keywords: Switched systems, Self-triggered control, Optimal control, Data-processing, Data acquisition, Time-delay, Probability of information loss

1. INTRODUCTION

There is nowadays a growing industrial interest in modeling data-processing units in the control loop, rather than assuming that these are ideal or account for the worst case. This is especially relevant in high-end applications and in data-intensive applications, such as big data and image-/vision-based control. In such applications, the data-processing element is a non-trivial component that converts large quantities of measurement data to control-relevant information. Typically, data-processing units are not limited to only one processing method, but many are available. Several characteristics can be included in the models of those processing methods, such as delay, accuracy of information, and the probability of acquiring information, often obeying trade-offs between the characteristics. Typically, once the characteristics of the processing methods have been identified, a single method with reasonable trade-offs is selected for implementation.

Recently, in van Horssen et al. (2015), we proposed to switch between data-processing algorithms on-line to improve closed-loop performance. In van Horssen et al. (2015), we have considered the trade-off between speed, modeled by the processing rate at which a given method can run, and accuracy, modeled by the noise characteristics (covariance matrix) of the processed data. In this paper, we tackle another important trade-off present in selecting data-processing algorithms, namely the trade-off between processing delay and probability of data-loss, i.e. the probability of acquiring control-relevant information from the data. In fact, if more processing time is allowed, the probability that useful information is obtained typically becomes higher, at the cost of a larger delay. Compared to the previous work, several new challenges are addressed in the design of the switching policy for this new trade-off, which are described shortly.

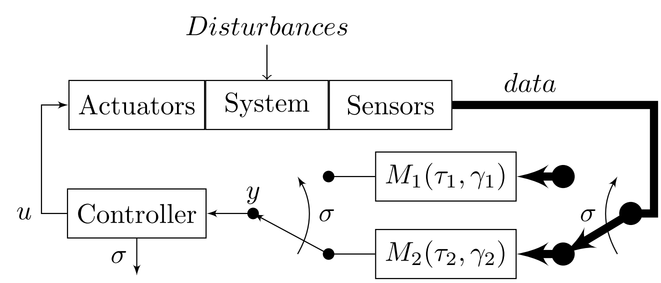

Fig. 1. Control loop with two data-processing algorithms

We consider the interconnection of a physical system with sensors and actuators, a data-processing unit consisting of several data-processing methods, and a digital controller in a feedback structure, as depicted in Fig. 1. The data-processing algorithms, or methods, acquire the data from the same sensors, but the way they produce control-relevant output varies. Each data-processing method is characterized by the incurred processing delay and the probability of having a correctly processed measurement. Only one processing method is allowed to be active at any given time, which is consistent with typical limitations on processing power. The goal is to design a switching and control policy to achieve a better closed-loop performance than the typical approach of selecting and implementing only the fixed method with best performance. Although only two methods are depicted, the results presented in this paper are valid for a higher number of processing methods.

2405-8963 © 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.10.409

Building upon available results in optimal control theory (Åström (1970); Schenato et al. (2007)) and ideas from (approximate) dynamic programming (Bertsekas (2005); van Horssen et al. (2015); Antunes et al. (2012)), we establish a switching and actuation policy that achieves improved closed-loop performance compared to the typical non-switching approach. To guarantee this improvement, a condition is used to establish the best non-switching policy, which is different from the assumption made in van Horssen et al. (2015) (see Remark 2). Since high-tech systems are typically resource-constrained, several suggestions are made towards efficient implementation of the method. Monte Carlo simulations for a second-order system illustrate the effectiveness of the method and the achievable performance improvement.

While the ideas of the present paper and of van Horssen et al. (2015) are, to our best knowledge, novel, there is some related work available in literature. Switching approaches to schedule measurements from different sensors have been considered previously, e.g. for sensor data scheduling (Wu et al. (2013); Kouchiyama and Ohmori (2010); Molin and Hirche (2009); Leong et al. (2015)). The recent self-triggered (Araújo et al. (2011); Antunes et al. (2012); Gommans et al. (2014)) and event-triggered (Wu et al. (2013); Rabi et al. (2008); Molin and Hirche (2010)) approaches to schedule transmissions in a control loop also exploit switching to improve the control performance. The relation between delay and information loss was addressed using a different approach in Demirel et al. (2015). Dropouts in the optimal control context are addressed in Schenato et al. (2007). The problem of selecting which part of the data is most relevant is considered in sensor management Hero and Cochran (2011), sensor fusion, and sensor selection literature. An alternative tool to construct switching and control policies is the embedding method (Bengea and DeCarlo (2005); Vasudevan et al. (2013)).

Besides tackling a different trade-off with respect to van Horssen et al. (2015), the present paper addresses the following challenges. No restricting relation is assumed between the delays of the different processing methods, leading to aperiodic sampling (see Remark 1). The new result allows asynchronous decision intervals, i.e. future decisions instances are not fixed in time (see Remark 3). Uncertainty of acquiring useful processing results inhibits regular innovation of the state information.

The problem formulation is given in Section 2. Section 3 explains the proposed methodology, provides the main result, and gives details on the implementation. A numerical example in Section 4 illustrates the benefits of the proposed method for a second-order system.

2. PROBLEM FORMULATION

This section describes the plant, the cost criterion, and the measurement and actuation methods used, leading to the problem formulation.

2.1 Plant and performance criterion

Let a linear stochastic system be described by the differential equation

$$\frac{d}{dt}x_C(t) = A_C x_C(t) + B_C u_C(t) + B_\omega \frac{d\omega}{dt}, \tag{1}$$

where $x_C(t) \in \mathbb{R}^{n_x}$ is the state and $u_C(t) \in \mathbb{R}^{n_u}$ is the control input at time $t \in \mathbb{R}_{\geq 0}$, and ω is an n_w-dimensional Wiener process with incremental covariance $I_{n_w}dt$ (cf. Åström (1970)). We assume that (A_C, B_C) is controllable and B_C has full rank. The initial condition is a Gaussian random vector $x_C(0) \sim \mathcal{N}(\bar{x}_0, \Phi^{x_0})$.

Performance of the system is measured by the average cost function, as in the linear quadratic Gaussian (LQG) framework, and is described by

$$J_C^a := \limsup_{T\to\infty} \mathbb{E}\left[\frac{1}{T}\int_0^T g_C(x_C(t), u_C(t))dt\right], \tag{2}$$

where $g_C(x, u) := x^\intercal Q_C x + u^\intercal R_C u$, with positive semi-definite and positive definite matrices Q_C and R_C, respectively. Additionally, we assume that the pair $(A_C, Q_C^{\frac{1}{2}})$ is observable.

2.2 Measurements from data-processing

At *sampling times* $t_\ell, \ell \in \mathbb{N}$, with $t_0 = 0$, a new sample of raw data pertaining to the plant is taken. At this time, a data-processing method $\sigma_\ell \in \mathcal{M}$ is activated to distill information that is relevant for feedback control. In this section, we assume, for simplicity, that $\mathcal{M} = \{M_1, M_2\}$ and we will refer to the processing methods by their indices $\{1, 2\}$. Furthermore, only one method may be active at a given time.

After a certain method-dependent delay incurred by the choice of processing method

$$\tau_\ell := \bar{\tau}_{\sigma_\ell} = \begin{cases} \bar{\tau}_1, & \text{if } \sigma_\ell = 1, \\ \bar{\tau}_2, & \text{if } \sigma_\ell = 2, \end{cases} \quad \bar{\tau}_{\sigma_\ell} \in \mathbb{R}_{\geq 0}, \tag{3}$$

the system provides new information y_ℓ to the controller.

The new information, which arrives at the controller at $t_\ell + \tau_\ell$, contains either information about the full state of the system at the sampling time, or no information at all, depending on an indicator $\gamma_\ell \in \{0, 1\}$, i.e.

$$y_\ell := \begin{cases} x_C(t_\ell), & \text{if } \gamma_\ell = 1, \\ \emptyset, & \text{if } \gamma_\ell = 0. \end{cases} \tag{4}$$

Upon information arrival, a new sample is taken, i.e. $t_{\ell+1} = t_\ell + \tau_\ell$.

Apart from the delay, the processing methods are distinguished by the probability that they will provide information. This property is modeled by the Bernoulli distribution of γ_ℓ for each method. In particular, we have that

$$\Pr(\gamma_\ell = 1 \mid \sigma_\ell) =: \bar{\gamma}_{\sigma_\ell} = \begin{cases} \bar{\gamma}_1, & \text{if } \sigma_\ell = 1, \\ \bar{\gamma}_2, & \text{if } \sigma_\ell = 2. \end{cases} \quad \bar{\gamma}_{\sigma_\ell} \in \mathbb{R}_{(0,1]}, \tag{5}$$

Typically, when the processing methods are given a shorter processing time to compute the output, they have also a higher probability of not producing an output. For two methods, this can be captured by the properties $\bar{\tau}_1 > \bar{\tau}_2$ and $\bar{\gamma}_1 > \bar{\gamma}_2$, which can be generalized to several processing methods by a proper ordering.

Remark 1. An important challenge introduced in this setting with respect to van Horssen et al. (2015) is that, by