EDITORIAL

Special issue on ‘Applications of Continuous-Time Model Identification and Estimation’

1. Introduction

Within the control and systems engineering community, system identification refers to the whole process of constructing a mathematical model for a dynamical system from measured input/output data or from a combination of such data and prior knowledge. Dynamical models obtained in this manner are useful for tasks such as enhancing physical understanding, analysing system properties and performing simulation, prediction, filtering, state estimation, monitoring and fault diagnosis, as well as control system design. Such models are usually formulated in terms of differential equations, or transfer functions in the differential operator, because the physical laws on which the models are based are normally synthesised in terms of differential equations based on natural laws, such as the conservation equations and laws of motion. Therefore, it is not surprising that until the 1960s, most control engineering theory and practice were based on continuous-time models, and early research on the statistical modelling of dynamic systems for the purposes of control system analysis and design was based on the identification of continuous-time transfer function models (see e.g. Young, 1970, and the prior references therein).

This situation changed during the 1960s, however, when pioneering research by control engineers, such as Aström and Bohlin (1966), and statistical time-series analysts, such as Box and Jenkins (1970), developed powerful maximum-likelihood methods for estimating the parameters in alternative discrete-time models, based on modelling in terms of transfer functions in the backward shift operator and the associated difference equations, rather than differential equations. While these developments led to models whose parameters are dependent on the sampling interval and so lose their immediate physical interpretation, they attracted a great deal of attention over the next 30 years motivated, in part, by the digital revolution that characterised this period. During this same time, however, research proceeded on the development of statistical methods for the identification of continuous-time models (see e.g. Garnier & Wang, 2008; Garnier, Mensler, & Richard, 2003; Garnier, Söderström, & Yuz, 2011; Rao & Unbehauen, 2006; Unbehauen & Rao, 1990, 1998; Young, 1981, 2011; Young & Garnier, 2006, and the references therein), but this was largely obscured by the much greater amount of research effort devoted to modelling and control system design devised in terms of discrete-time models.

Fortunately, in our opinion, the last decade has witnessed a resurgence of interest in direct continuous-time modelling from sampled data. This is evidenced, for example, by the recent addition of direct continuous-time model identification methods in the latest version of the well-known Matlab System Identification Toolbox (Ljung & Singh, 2012): the methods that add to those existing methods of continuous-time model identification that have been available for some considerable time in other, freely available toolboxes, such as CONTSID and CAPTAIN (see the first paper of this special issue). Of course, continuous-time models should be considered as complementary to discrete-time models, and potential users should be aware of the advantages/limitations of each approach, so that they are able to select the most appropriate methodology, or combination of methodologies, to solve their modelling and control problems.

Although continuous-time system modelling from sampled data is now mature, so that computer-based methods of maximum-likelihood and optimal instrumental variable estimation are freely available to the potential user, it is not a ‘spectator’ sport. Optimal methods of estimation are only valuable if they are robust and ‘work’ in practice. And the only way to discover the strengths and limitations of the various techniques is to first become familiar with how they are utilised when applied to real-time series data, and then thoroughly evaluate their worth in truly practical applications. With this in mind, the present special issue aims at both assessing the current state-of-the-art in the field of continuous-time model identification and revealing the capabilities of current methods when applied to real and challenging applications.

2. Content of the special issue

The first paper is by ourselves, acting in our role as guest editors of this special issue, so it tries to set the scene for subsequent papers by discussing the advantages of direct continuous-time model identification, illustrating these with the help of modelling examples based on the analysis of real sampled data derived from different physical systems in areas ranging from the environment to engineering.

The next paper considers the identification of a class of continuous-time hybrid systems which involve both continuous-time and discrete-time dynamics. The paper by Ricardo Aguilera, Boris Godoy, Juan Carlos Aguero,
Graham Goodwin and Juan Yuz investigates the use of the expectation–maximisation (EM) algorithm to identify δ-operator state-space models from fast sampled data. The proposed approach is successfully applied in the area of power electronics.

Then, Jeremy Vyassettes, Guillaume Mercere, Pierre Vacher and Raymond de Callafon present a frequency domain identification approach for modal analysis of aircraft structures during flutter flight tests. The proposed approach is applied to real data recorded during an in-flight flutter test performed on a military aircraft.

The paper by Scott Moura, Jan Bendsten and Victor Ruiz focuses on modelling aggregated thermostatically controlled loads (TCL) in order to facilitate control schemes. In particular, the dynamic behaviour of the temperature distribution in large TCL populations is examined. Two partial differential equation (PDE) based models for the temperature distribution evolution are proposed. A passive parameter identification scheme and a swapping-based identification scheme are derived for the PDE model structures.

The next paper, by Arturo Padilla, Juan Yuz and Benjamin Herzer, considers model-based control strategies for inland vessel navigation systems and develops continuous-time system identification schemes for estimating the steering dynamics of a ship. Data collected from the ship during navigation on a river are successfully used to identify the yaw and drift dynamics when the stochastic disturbances in the river are not negligible.

The contribution by Toom Oomen presents a general framework for continuous-time system identification and sampled-data control. It is illustrated by its application to an industrial wafer stage system with aliased resonance phenomena.

The next three papers consider the application of dynamical systems and control theory in the development of innovative interventions in health care and medicine. First, Kevin Timms, Daniel Rivera, Linda Collins and Megan Piper show how data-based continuous-time model identification is useful for the analysis of smoking cessation interventions and for comprehensively describing the process of smoking cessation.

Then, Marzia Cescon, Rolf Johansson, Eric Renard and Alberto Maran show how predictor-based subspace methods of continuous-time model identification can be used to obtain personalised models of type 1 diabetes blood glucose dynamics from patient data.

In the last contribution, Harald Kirchsteiger, Rolf Johansson, Eric Renard and Luigi del Re present a regularised continuous-time parameter estimation scheme for an arbitrary number of experiments. The proposed method is successfully applied to irregularly sampled data from type 1 diabetes patients.

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