Introduction

Chapter 1
Preface

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"In theory, there is no difference between theory and practice. In practice, there is."
Yogi Berra

1.1 Introduction

One of the main challenges of modern engineering applications is how to effectively handle the increasingly large amount of data and information available in today's complex dynamical systems [47]. Data can be used for mathematical modeling but also for monitoring, filtering and control.

For instance, it is often estimated that more than 75% of the costs associated to an advanced control project goes into accurate mathematical modeling [19]. For some real plants, some work might be dedicated to devise a model of the physics underlying the process, but nowadays most of the efforts are usually devoted to data-driven modeling, that is, experiment design and implementation, model learning from data and data-driven validation.

Within this framework, *System Identification*, namely the science of deriving dynamical models from Input/Output (I/O) measurements, has played a key role throughout the last 50 years. The traditional objective of system identification has been that of finding the model which best fits the data, so that model-based filters and controllers could be designed standing on the assumption that the identified mathematical description coincides with the real system (the so-called *Certainty Equivalence Principle*, or *CEP*).

Application-oriented system identification. Since - quoting G. Box - "all models are wrong, some are useful" [8], the above approach may lead to detrimental effects when applied to real world setups. In fact, since modeling usually represents only the intermediate phase of a two-step design procedure, modeling errors may seriously affect the performance achieved with the system of interest, e.g., a model-based controller or a virtual sensor. For this reason, robust approaches have

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been developed, which take into consideration not only a nominal model but also a description of the uncertainty region [44, 56].

In any case, the model (and the related uncertainty region) which best fits the data might be a bad choice for model-based design, in that the loss function accounted for during the identification phase (typically, a norm of the data-fitting error) does not usually coincide with the final application-oriented cost to minimize (e.g., in control it is a measure of the mismatch between the desired closed-loop behavior and the achieved one). Nonetheless, robust design is safe but may lead in some cases to very conservative performance, depending on the size of the uncertainty set. Also, deriving the required uncertainty region model may be a difficult task, especially in the case of nonlinear system. Some additional knowledge about the specific domain or the model application is then *necessary* to deal with real-world systems in an effective way.

Identification for control. Based on the above observations, in the 90's, a few leading experts in system identification started to analyze the interplay between identification and control, see, *e.g.* the plenary [18] at the 1991 IFAC Symposium on System Identification. The new field originated from such studies, called *Identification for Control* (*I4C*), proposes a change of perspective, in which "modeling" is seen as *a design problem*. In other words, one could think of designing the identification process in order to find a model (and an uncertainty set) which does not necessarily fit the data at best, but which obtains satisfactory closed-loop performance when the (robust) model-based controller is applied to the real system, by - at the same time - minimizing the level of conservativeness.

An alternative yet appealing approach is to map the data directly onto the controller parameters. From now on, this approach will be referred to as *Direct Data-Driven Control* (*D^3C*) [6]. D^3C can be seen as a subfield of I4C, in which the identification process is designed to that the system to identify from data is directly the controller. An interesting feature of this approach is that the control design stage is automatically incorporated into the modeling part, thus simplifying the procedure.

The overall I4C rationale is depicted in Figure 1.1 (solid lines). Unlike standard identification and control, the modeling step is "control-oriented", in that data are mapped onto the model which is best suited for control design. In the same figure, the D^3C alternative is illustrated using dashed lines.

Identification for filtering. Similarly to what happens in I4C, also in the context of *Identification for Filtering (I4F)* two main approaches can be distinguished: the two-step approach, where first a model of the system of interest is identified from data and then a filter/observer is designed from the identified model; the direct approach, where the filter/observer is directly designed from the available data. As discussed in [51], the two-step approach is in general not optimal, due to the following reasons: 1) only approximated models can be identified from measured data, and a filter which is optimal for some identified model may display a large estimation error when applied to the real system; 2) in the case of nonlinear systems, designing a computationally tractable optimal filter is in general difficult, and often only approximate filters can be derived, whose accuracy and/or stability are not guaranteed. Evaluating how these two sources of approximation affect the filter estimation accu-

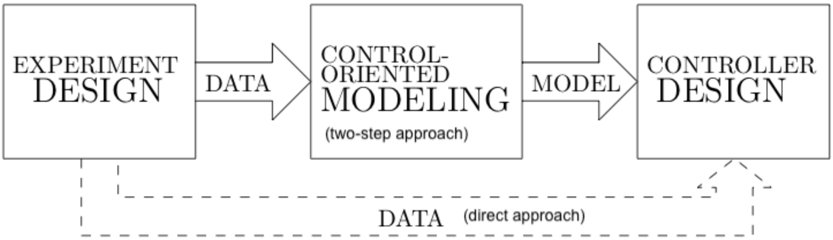

Figure 1.1 *The I4C design procedure based on experimental data (solid lines). Firstly, data are mapped onto a model of the system, by taking the control objective into account. Then, the controller is designed based on the identified model and, possibly, an estimate of the uncertainty set. If a D^3C approach is adopted, the data are directly mapped onto the control parameters (dashed lines).*

racy is a largely open problem. Note that robust filtering does not provide at present an efficient solution to the filter design problem. Indeed, the design of a robust filter is based on the knowledge of an uncertainty model (e.g., a nominal model plus a description of the parametric uncertainty). However, identifying reliable uncertainty models from experimental data is an open problem, especially when nonlinear systems are involved. Moreover, in the case of nonlinear systems, designing a computationally tractable robust filter is in general hard (see [49], [39]) and approximate filters are used [69], [12].

The direct approach can overcome these issues, allowing the design of optimal filters for linear and nonlinear systems [51], [53]. Another advantage of the direct approach is that it is in general simpler.

In summary, in I4F, we can say that the direct approach may be more convenient than the two-step approach in many situations. A similar statement does not hold in I4C, where the direct approach may present some advantages with respect to the two-step approach but, in some situations, the latter may be more convenient (see the discussion in Section 1.2).

The overall I4F rationale is depicted in Figure 1.1.

1.2 State of the art

System identification is the science of learning dynamical models from experimental data. A thorough review of the state of the art for this discipline would take too much space and would anyway sound sketchy and incomplete. Therefore, after a brief introduction on the topic, we will hereafter focus on the interplay between system identification and model-based design applications, to introduce the key technical difficulties which still limit the performance of many real-world filters and controllers.

The first steps. To start with, consider that system identification goes as far back as the work of Gauss and Legendre in the late 18th and early 19th century. Until the

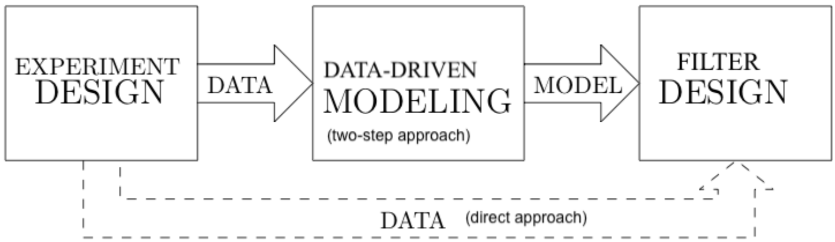

Figure 1.2 The I4F design procedure based on experimental data (solid lines). Firstly, data are mapped onto a model of the system, by taking the control objective into account. Then, the filter/observer is designed based on the identified model and, possibly, an estimate of the uncertainty set. If a direct approach is adopted, the data are directly mapped onto the filter/observer (dashed lines).

late 1950's, the field had been mainly developed by mathematicians, statisticians, time-series analysts and econometricians. The main reason why control engineers had not been attracted by the discipline was that control design was mostly based on Bode and Nyquist plots, Ziegler-Nichols charts and other graphical design methods.

In the 1960's, thanks to the work by Kalman [31, 32], graphical design techniques were rapidly replaced by more effective model based (certainty equivalence) control design. Parametric models became the central focus of attention, and the development of parametric identification techniques naturally followed that of model based control design.

The founding year of modern system identification is definitely the year 1965, with two different milestones. The Ho-Kalman paper [33] provided the first solution to the determination of a minimal state-space representation from impulse response data and paved the way for the development of subspace identification [74]. The Åström-Bohlin paper [3] introduced the Maximum Likelihood framework developed by time series analysts into the control community and gave rise to the successful PEM framework [36].

For more than 20 years, system identification has been at the service of control engineers, but developed as a science strictly distinct from control theory. The aim of identification was only that of finding a good model of the plant: the better the model (*i.e.*, the closer to the "real" system description), the better the final control performance (see again Figure 1.1). All problems related to inaccurate modeling had to be handled in the control design phase, *e.g.*, by employing robust techniques.

Identification as a design process. It was in the early 1990's that, within the identification community, the faith that the true system could be modelled almost perfectly started to waver. In those years, providing a description of the model uncertainty became at least as important as computing the "nominal" (*i.e.*, most likely) model: people started to see identification as something to *design* with a specific model application in mind [18]. The main rationale behind this change of perspective was that, if model uncertainty is unavoidable, it is smart to *shape* the error in such a way that its effect is practically negligible for the closed-loop system. This objective can be achieved by playing, *e.g.*, with the experimental conditions, the selection of the identification cost and/or the model complexity [19]. All the approaches with these features were put inside the set of I4C methods.

It must be said that the first analyses of the interplay between identification and control were already provided by Fel'dbaum in the 1960's. Using the concept of "dual" control, Fel'dbaum showed that, when controlling a system whose parameters are unknown, the control effort must pursue the dual goal of "investigating", *i.e.*, obtaining information about the system, and "directing", *i.e.*, piloting the system towards the best achievable state [15]. Unfortunately, the solution of the optimization problem trading off investigation and directioning proved to be computationally intractable, even in the simplest cases. Moreover, the whole dual control theory was essentially developed for the unrealistic case where the structure of the true system is known, and the system is in the model set. The above problems made dual control very hard to use in real applications. The same drawbacks were shared by the early attempts in adaptive control [4], in which the model parameters are adjusted at every time instant and the analysis of closed-loop properties is even more complex.

Conversely, the studies carried out in the 1990's led to the development of simpler design schemes, in which the model is found by minimizing some control-oriented cost and the controller is derived accordingly. In such studies, it was also observed that, since any "control-oriented" criterion implicitly requires the knowledge of the controller that will be implemented on the real system, any design scheme of this sort can only be iterative: namely, at each iteration a model is identified from data obtained on the real plant on which the most recent controller is acting; the controller parameters are in turn computed from the most recent model. As a result, the succession of nominal models have a bias error distribution that is tuned for control design. This means that the (typically low order) nominal models have a model error that is small in the frequency areas where it needs to be small for the design of a better controller, typically around the present cross-over frequency [19].

Within the I4C field, many observations were made which turn out to be very useful for everyday engineering, *e.g.*: a closed-loop identification experiment may be more effective than an open loop one [27], identification methods delivering accurate error bounds may provide models not well suited for robust control design, and many others.

Despite the success of I4C in a number of real-world process control applications, it was shown in [28] that, even with the simplest control performance criterion, such iterative schemes are not guaranteed to converge to a minimum of the control performance criterion over all models in the chosen set. This may even cause the iterative parameter adjustment scheme to drift to a controller making the closed loop system unstable. Therefore, model validation for control and controller validation criteria were introduced to guarantee the stability of the closed-loop [20]. After that, most of the efforts have been devoted to model error modeling, see, *e.g.*, [17, 37], and, above all, to a (renewed) interest in optimal experiment design, aimed to take the most from the available data from a control-oriented perspective, see, *e.g.*, [5,75].

Notwithstanding all the above valuable efforts, after more than 20 years from the foundation of I4C (say, the plenary [18] at the 1991 IFAC Symposium on System Identification), identification and control are far from being processes synergically designed. On the one hand, robust control is still mainly based on hard bounds on model uncertainty [56], which are different from the soft ones provided by the most widely used (*i.e.*, stochastic) identification methods. On the other hand, identification people have not yet provided an automatic modeling procedure able to give guarantees for the real-world closed-loop systems. In fact, some interesting validation procedures have been proposed for model-based controllers, but no algorithm is currently able to embed the problem specifications inside the design procedure.

Moreover, as already mentioned in Section 1.1, limitations are given in terms of admissible systems (linear time-invariant), identification approaches (PEM), validity of the results (infinite dataset), convergence of the iterative algorithms (not guaranteed) and systematic use of the prior knowledge. For all the above reasons, I4C cannot be considered yet a solid methodology for automatic data-driven controller design.

Controller identification. As an alternative to control-oriented model identification, within the past 20 years, I4C people have produced also a number of methods which, instead of considering the control objective inside the identification phase, directly map the data onto the controller parameters (D^3C [6]). In this way, modeling does not need to be designed to optimize the control performance, because it is actually fully skipped.

Some of these methods already existed before the 1990's and were adaptive design methods; in other words, in these techniques, the controller parameters are adjusted at each time instant, depending on the new measurements coming from the closed-loop system. The major difference between these algorithms and the more classical model-based adaptive control is that the controller parameters update rule does not require a parameterization of the plant [48]. However, being adaptive schemes, the analysis problems of classical adaptive control were shared also by these approaches. The same holds for more recent D^3C methods like the Unfalsified Control approach [67], which anyway can be considered as a big leap towards modern direct design of feedback controllers from data.

Instead, the methods proposed as alternatives to iterative identification and control after the foundation of I4C are *offline methods*: the controller is designed based on the information contained in one or more bunches of experimental data, but the controller is fixed while the closed-loop system is operated. This feature allows a simpler analysis of the closed-loop and avoids the typical problems of adaptive control. Among these methods, Iterative Feedback Tuning (IFT, [25]) involves iterative optimization of the parameters of a fixed-order controller according to a data-driven estimate of the gradient of the control performance criterion. In Iterative Correlation-based Tuning (ICbT, [34]), the controller parameters are instead tuned iteratively either to decorrelate the closed-loop output error between the desired and the achieved closed-loop systems with the external reference signal (decorrelation procedure) or to reduce this correlation (correlation reduction).

Both the above methods require several experiments (especially in the multivariable case for IFT [24]) to update the controller parameters. Instead, in Virtual Reference Feedback Tuning (VRFT, [9]) and noniterative Correlation-based Tuning (nCbT, [35]), the controller is designed in “one-shot”, by employing a single set of data. Since a single set of data is also the starting point of many model-based control design methods, this feature allowed I4C researchers to carry out a fair comparison between D^3C and certainty equivalence design (namely, classical system identification plus model-based control).

Such a comparative analysis showed that “going direct” certainly gives some advantages in fixed-order controller tuning, like avoiding model parameterization and model error modeling. At the same time, some drawbacks can be listed, among which the major ones are the following: (i) only sufficient (and overly conservative) conditions are currently available to guarantee closed-loop stability [73], (ii) direct design is statistically less efficient than model-based design with correct model parameterization [26, 66], (iii) if the controller can be freely chosen, the problem of model parameterization is not skipped, but simply transformed into that of controller selection (the aim, in this case, is to select a controller class including the controller achieving the desired closed-loop properties).

It should be stressed that, unlike more classical I4C, in D^3C the fact that the achieved closed-loop is uncertain due to the randomness of the dataset has never been analysed in detail (uncertainty assessment in D^3C is not needed for control design). Nevertheless, as an advantage over more classical I4C, control of nonlinear plants has been more deeply investigated, see, *e.g.*, use of IFT with nonlinear systems [23], nonlinear VRFT [10], iVRFT [63], direct control of Linear Parameter-Varying (LPV) systems [64] and Direct FeedbacK control (DFK) [50]. Also in the nonlinear setting, the methods lack some important features. For instance, stability guarantees are given only in DFK, which however has been developed within a set-membership framework and therefore relies on bounded noise hypothesis without exploiting any prior knowledge on the noise distribution. Moreover, the DFK method can be used only in the restrictive case where the full state is measurable.

Therefore, despite several successful practical applications (see, *e.g.*, [55,58,61, 62, 65, 78], also in D^3C a lot of research work still needs to be done to provide a general data-driven methodology with reliable performance guarantees.

Filter identification. As discussed in Section 1.1, and analogously to what happens in I4C, two main approaches to I4F can be found in the literature: the two-step approach, based on model identification from data and subsequent filter design, and the direct approach, where the filter is directly identified from data, avoiding the model identification step.

The two-step approach is in general not optimal, especially in the case of nonlinear system, where designing an effective filter is in general a hard task [51]. Conversely, the direct approach may allow the design of filters with suitable optimality properties, even for complex nonlinear systems. The direct approach is based on the simple idea that a filter/observer is a dynamic system whose inputs are the input and output of the system of interest and the output is an estimate of the system state variables (or a function of them). Hence, it is more efficient to identify this filter/observer system directly from data using a suitable identification method (linear or nonlinear), rather than designing it on the basis of a model identified from the same data, whose uncertainties and/or nonlinearities may strongly affect the filter estimation accuracy.

Filters/observers are often called "virtual sensors" or "soft sensors", since they can be used in place of (or in addition to) the more traditional physical sensors, yielding relevant advantages such as cost reduction, redundancy, increased robustness and safety, and space saving.

In the literature, several works on direct filter identification for Linear Time Invariant (LTI) systems [38, 42, 43, 76, 79] and Linear Parameter Varying (LPV) systems [52, 59] can be found. However, the majority of works regard nonlinear systems. Indeed, the direct filter identification approach has proven to be a key enabler to solve filter design problems for nonlinear systems that cannot be solved using standard techniques. In the nonlinear context, several state-of-the-art approaches can be found: neural network approaches [2, 71, 77], set membership approaches [41, 53], piecewise affine approaches [57], approaches based on radial basis functions [29] and gray box approaches [11]. A limited number of these works provide theoretical/methodological analyses/results [14, 16, 38, 41, 43, 45, 51, 53, 57, 70, 76, 79]. Most of works are concerned with numerical analyses and/or applications of practical interest in different fields of science and technology, see, among many others, [1, 2, 7, 11, 13, 21, 22, 29, 30, 40, 46, 54, 60, 68, 71, 72, 77].

1.3 Goals and structure of the book

Although very appealing, the above data-driven approaches suffer from some important limitations, which make them not yet competitive with state of the art model-based design. At the same time, the cutting-edge identification technologies, like nonparametric identification, are not yet ready to be applied for modeling of real-world systems. More specifically, the major limitations of current state of the art, also following the discussion of the previous section, can be listed as follows.

- recent nonparametric identification approaches have been mainly developed for linear time-invariant plants, while most real-world systems exhibit a linear parameter-varying (LPV) behaviour or specific nonlinearities (e.g. Wiener systems);
- when dealing with real-world applications, the science of learning and identification usually mixes with the art of domain-expert people. This should reflect into practical hints that are often missing in the scientific papers;
- direct data-driven control design has been mainly developed in the linear SISO case, while modern systems are usually characterized by coupled nonlinear dynamics;
- many specific design problems like that of dynamic sensor and fault-detection usually rely on a (uncertain) model of the plant;
- data-driven design problems may rely on the knowledge of some system parameters, which is milder than the knowledge of the full system dynamics. In those cases, it would be suitable to directly identify those parameters from data. This

is the case, e.g., of the H_∞ norm usually employed to characterize a bound on the modeling error;
- although many data-driven techniques have been proposed, theoretical and experimental analyses are missing in the literature with the aim to compare the eventual performance of different methods on challenging engineering applications.

Facing the above issues, this book proposes a number of contributions that try to overcome the current limitations of the state of the art to make the direct data-driven design technology competitive with model-based alternatives. Moreover, challenging modeling problems in modern engineering systems are addressed in a novel way to show both the methods and the implementation tricks that potentially make an application successful.

In particular, the book is structure in two parts. The first part (Chapters 1-4) is dedicated to *application-oriented system identification* and proposes 4 contributions in which existing techniques are complemented with additional tools to deal with challenging real-world problems. The second part (Chapters 5-12) is devoted to *data-driven design* and deals with the estimation of application-oriented parameters as well as direct identification of controllers and filters within complex scenarios.

Part 1 is entitled **Data-driven modeling** and is composed as follows.

- **Chapter 1** extends non-parametric identification to Wiener systems. A tractable convex relaxation of the original problem is derived to handle cases involving systems with high dimensional outputs. Such a theoretical extension is motivated by (and validated on) a classification problem using video data.
- **Chapter 2** deals with the wing flutter identification problem in a situation of poor information. In particular, a LPV approach is proposed and theoretically analyzed.
- **Chapter 3** proposes LPV identification of a web-winding machine using multi-local models. Experimental issues when working with real-world data are discussed in detail.
- In **Chapter 4**, an electrochemical impedance spectroscopy (EIS) for Li-ion batteries, based on system identification techniques, is discussed together with the main implementation issues.

The title of Part 2 is **Data-driven filtering and control**. The following chapters are included.

- **Chapter 5** considers the problem of dynamic measurements in metrology, that is the fact that sensors can be characterized as dynamical systems and, as such, affect the quality of the measurement. In this chapter, the measurement is then dynamically compensated from data without relying on the full model of the sensor.
- **Chapter 6** reviews the latest developments of Iterative Learning Control (ILC) by outlining a range of design approaches for multivariable ILC with a focus on cases with limited model knowledge.

- **Chapter 7** deals with the data-driven estimation of the H_∞ norm of a LTI system. This is an important issue in real-world problems in which a bound on the modeling errors should be provided together with the nominal model (e.g., for robust control purposes).
- **Chapter 8** compares two direct data-driven control design approaches, developed within a statistical and a deterministic setting, respectively: Virtual Reference Feedback Tuning (VRFT) and Set-Membership controller Tuning (SMT).
- **Chapter 9** addresses the difficult problem of direct Fisher matrix approximation from data. Such a matrix is very useful in system identification for benchmarking the achievable performance, as it provides a lower bound for the variance of maximum likelihood estimates.
- In **Chapter 10**, a method to design feedback controllers from data for linear constrained systems is proposed. The method is based on a novel application of receding horizon policies within a model-free scenario.
- **Chapter 11** presents an approach to fault detection for nonlinear dynamic systems, based on the recently introduced quasi-local Set Membership identification method.
- In **Chapter 12**, a data-driven controller design methodology is developed, that guarantees $\mathcal{H}_\infty$ performance and closed-loop stability for linear systems that are subject to non-linear distortions.

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