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PHYSICS-AWARE SOFT-SENSORS FOR EMBEDDED DIGITAL TWINS

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Let us call a *Physics-aware soft sensor* the numerical algorithm that performs an indirect measurement by exploiting a physico-mathematical model plus a possible data-driven extension, within an estimation algorithm. In this sense, a physics-aware soft sensor solves a problem which is the combination of an inverse problem and a learning problem. It can conveniently be seen also as a generalization of an inverse problem, where part of the model is unknown and its construction is data driven. We will present two examples in mechanical vibrations analysis and in inverse heat transfer problems.

Keywords: *soft-sensors, inverse heat conduction problems, forcing term estimation, deep unfolding, sparse recovery*

1. Introduction

According to [1], Embedded Digital Twins, that is the virtual representation of physical systems that runs in an embedded system, are deployed on the edge within the embedded software stack to realize e.g. virtual sensors to enrich available information about physical variables and parameters that cannot be provided by direct physical measurements. These lacking measurements are estimated, at least roughly, by an algorithm that processes the available data, usually called a soft sensor. In the literature about soft-sensors, a strong emphasis is frequently put on black-box, data driven algorithmic techniques.

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- model complexity,
- interactions with the environment,
- centrality of physically measured variables in the virtual measurement process.

We start by briefly describing a couple of applications in electronic household appliances, involving a large number of items produced and tight computing resources. In the first one, i.e. indirect measurement of a mechanical load, the soft-sensor is physics-aware, while in the second one, indirect measurement of the load humidity during a drying process, the soft-sensor is data-driven (a neural network). We will briefly present also the technological aspects involved in computing and in model tuning of each single item at the production line. Then, we recall the recent, enormous improvement in computing performances given by low-cost electronics and consequent algorithmic possibilities available today for embedded digital twins, even exploiting models with distributed parameters, governed by PDEs. We will present two examples in mechanical vibrations analysis and in inverse heat transfer problems. We conclude by discussing some relevant issues in industry, when dealing with physics-aware soft-sensors, mainly:

- amount of experimental data needed to develop the application,
- effort needed at a posterior extension of the soft-sensor to product variants,

and show a clear practical advantage of physics-aware soft sensors compared with pure data-driven ones, when a physico-mathematical model can be set up, at least for some relevant parts of the real system.

2. Physical parameters estimation of a mechanical system from audio source-separation

The empirical estimation of physical parameters in a mechanical system is commonly performed in the Fourier domain, by computing the Frequency Response Function (FRF) or a Short-Time Fourier Transform (STFT). This is made usually from vibration measurements, given by accelerometer sensors, strongly fixed to the vibrating medium.

Using a microphone instead of the usual accelerometer, imposes to separate the acoustic source created by the process to be monitored, from the acoustics generated by the environment. In this setting, the source tracking property of Deep NMF [2] becomes crucial. Indeed, the *deep unfolding* paradigm, and precisely the Deep NMF, can be conveniently used for physical parameters estimation of a mechanical system, in terms of:

- performance with respect to the corresponding linear method (i.e. the NMF or Nonnegative Matrix Factorization);
- flexibility to create new model configurations, thanks to the physical explainability of the basis functions used in the learning process.

We will show results from an ad-hoc synthetic database and a real example involving experiments from a machine tool operation.

3. Internal voids/material-changes estimation from thermographic inspection

In the second example we will describe the results of an ongoing project about the embedded digital twin of a bread-making production line, focusing in particular on a soft-sensor that uses a Kalman Filter to estimate a distributed heat source on a thermal inverse problem [3].

Here, the formation of internal voids due to yeast activity is estimated by indirectly measuring an equivalent distributed heat source, whose shape can be analytically computed [3]. Hence, the reference model for the Kalman Filter is the coupling of a Finite Element model for the heat transfer within the known material (bread) and a data driven model for the unknown, distributed heat source, based on the analytical study [3].

We show how this device of interpreting a hidden material change as a fictitious heat source [4] gives better results than a general, data-driven optimization acting on the bare temperatures prediction error, and we show that, having a theoretical insight on some features of the shape of these fictitious heat sources [4], it is possible to tune the reference model of a Kalman Filter that allows to get reasonable estimates at a considerably reduced computational cost, that make it applicable to embedded digital twins.

REFERENCES

1. Hartmann, D. and der Auweraer, H. V. Digital twins, *CoRR*, **abs/2001.09747**, (2020).

2. Hershey, J. R., Roux, J. L. and Weninger, F. Deep unfolding: Model-based inspiration of novel deep architectures, *arXiv preprint arXiv:1409.2574*, (2014).

3. Rinaldi, L., Giusteri, G. G. and Marcuzzi, F. Replacing voids with fictitious sources in heat conduction problems, *submitted*, (2023).

4. Dessole, M. and Marcuzzi, F. Accurate detection of hidden material changes as fictitious heat sources, *Numerical Heat Transfer, Part B: Fundamentals*, pp. 1–24, (2023).